IMPROVING ACCESS OF LOW-INCOME PEOPLE TO FORMAL FINANCIAL SERVICES: EVIDENCE FROM FOUR MICROFINANCE ORGANISATIONS IN KWAZULU-NATAL

VOLUME II

By

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DECLARATION

I hereby certify that, unless specifically indicated to the contrary in the text, this thesis is the result of my own original work

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CHAPTER FIVE

ECONOMETRIC MODELS OF CREDIT RATIONING AND LOAN DEFAULT FOR MFO1

This chapter outlines the theoretical background to the importance of lenders developing suitable technologies to reduce information asymmetries. Section 5.2 explains the objectives of the loan default analysis using sample data obtained from MFO1 over the period 1998 to 1999. The economic model specification for the analysis is given in section 5.3 followed by the sampling methodology and the definition of the dependent variable in section 5.4. Descriptive information about the sample data is briefly discussed in section 5.5, while the remaining sections review the results of the estimated models.

5.1 Theoretical Background

Lenders seldom have perfect information on the willingness of loan applicants to repay the loan and may also have difficulty in establishing the true circumstances leading to loan default. This is because of the information asymmetries that exist between the two contracting parties. The implication of such asymmetric information in credit markets is that the price (interest rate of credit) may not act as a market-clearing mechanism. Furthermore, lenders may credit-ration loan applicants, where this rationing may be in the form of additional collateral requirements or loan size and loan term rationing. The extent of the rationing depends on the level of information held by the two contracting parties and how effectively loan contracts can be monitored and enforced (Hoff and Stiglitz, 1990; Herath, 1996; Barham *et al.*, 1996).

It is thus important that lenders are able to reduce information asymmetries by overcoming the problems of adverse selection and moral hazard. Where a lender is not able to distinguish between potentially high-risk and low-risk loan applicants, there is a greater likelihood of accepting a high-risk loan applicant and incorrectly rationing the low-risk loan applicant. This leads to higher levels of default as more high-risk borrowers are accepted, forcing the lender to increase interest rates to cover increased costs associated with increased loan default. This may result in low-risk loan applicants opting out of the loan market, and it also increases the risk of the remaining pool of loan applicants applying for credit. This may impact negatively on lender profits (Stiglitz and Weiss, 1981).

Similarly, imperfect loan contract monitoring and enforcement may increase the likelihood of moral hazard. This negatively affects lender income and may force the lender to increase levels of monitoring or to require additional collateral to compensate for the greater loan default (Herath, 1996; Navajas, 1999a). Additional monitoring increases lender costs, while there may also be additional costs associated with evaluating collateral. This may encourage the lender to increase interest rates to compensate for higher costs, or credit may be rationed. Both of these effects have negative consequences for low-risk borrowers (Navajas, 1999a).

As outlined in Chapter 4, microfinance institutions have used different financial technologies to mitigate information asymmetries, the two main technologies being group- and individual-based lending. Where it is difficult and very costly to obtain information on individuals and the projects that require finance, and to monitor the performance of borrowers, MFOs have used group-lending technologies. A standard loan contract is offered with a set term and a set interest rate with individuals self-selecting into the program. To try and ensure that the group of borrowers is able to repay the loan, care is taken by the lender in selecting to finance those activities that generate sufficient incomes. Loan contracts are enforced by joint liability in which individuals within the group monitor each other to ensure contractual obligations are met (Besley and Coate, 1995; Navajas, 1999a).

The disadvantage of this type of technology is that only one standard loan contract is offered to potential borrowers. This may not necessarily meet the requirements of borrowers and may also penalize low-risk borrowers who could have obtained a better loan contract had the lender been able to screen individually for risk (Gonzalez-Vega *et al.*, 1997). In addition, if there are many 'free-riders' in the group who opt not to pay, there may be wholesale default in the group. Also, if the earnings within the group are positively correlated, as in agricultural lending, group loans may not necessarily reduce default risk (Besley and Coate, 1995).

Financial technologies that grant individual loans require that lenders screen loan applicants individually to assess loan repayment risk. Where the assimilation of information about the individual loan applicant rests within the group for group loans, the MFO is required to collect this information for individual loan applicants. Successful MFOs in Bolivia, such as Caja Los Andes and Financiera Calpia employ loan officers to collect information from loan applicants and perform some of the initial credit screening. The information is then processed and evaluated by a credit committee according to certain prescribed guidelines (Navajas, 1999b). Hence the knowledge about credit worthiness of loan applicants rests with the loan officers and members of the credit committee, and relies heavily on the localized knowledge that these individuals have about their clientele.

Successful MFOs in Indonesia used the localized knowledge of tribal chiefs to screen loan applicants, thus avoiding investment in technology and skills to screen loan applicants themselves (Chaves and Gonzalez-Vega, 1996). More advanced commercial lending institutions have employed sophisticated scoring technologies to assimilate and process information about loan applicants in order to provide loan officers with an indication of the potential risk of loan default. This process has been facilitated by access to suitable information to use in these scoring models (Schreiner, 1999; Hand and Henley, 1997). The type of credit assessment financial technology used, depends largely on the ease of access to information, the availability of collateral and the ability to enforce loan contracts.

To try and improve the ability of lenders to screen loan applicants, numerous studies have tried to identify factors that influence loan default. Few studies have specifically focused on identifying factors that influence loan default by small-scale agricultural borrowers, because information was not readily available. Early research by Igben (1978), Sanderatne (1978), Boakye-Dankwa (1979) and Okorie (1986) identified factors that influenced small-farmer loan repayment, primarily in Nigeria. Few of these studies had access to original data, with Sanderatne (1978) and Boakye-Dankwa (1979) relying on secondary survey data for their analyses. Aguilera-Alfred and Gonzalez-Vega (1993), Vigano (1993) and Hunte (1993) used more rigorous empirical models to estimate factors influencing loan repayment at the Agricultural Development Bank of the Dominican Republic, Caisse Nationale de Credit Agricole of Burkina Fasso, and the Guyana Cooperative Agricultural and Industrial Development Bank, respectively.

Local research by Lugemwa and Darroch (1995) and Kuhn and Darroch (1998) explored the loan repayment performance by short-term and medium-term borrowers at two agricultural credit banks in SA that received government subsidies. Later studies by Reinke (1998), Zeller (1998) and Schreiner (1999) focused on loan repayment performance at MFOs providing mostly non-agricultural credit to borrowers involved in small businesses. Although most of these studies do not provide models that are useful for credit scoring purposes because of the small sample size and the use of information that lenders do not readily collect or have available, they give some insight into factors that may require more consideration by lenders in the credit granting process. The model developed by Schreiner (1999) was a first attempt to develop a more rigorous empirical scoring model based on a very large sample of 10 555 loans disbursed by a microlender in Bolivia.

Due to the ready availability of data, numerous studies have investigated the loan repayment performance of commercial farm clients (see Turvey, 1991; Miller and LaDue, 1991; Mortensen *et al.*, 1988). Early work by Orgler (1970), Altman (1980), Dietrich and Kaplan (1982) and Reichert *et al.* (1983) focused on factors influencing loan repayment performance of commercial bank loans. Boyes *et al.* (1989), Greene (1992), Jacobson and Roszbach (1998) and Roszbach (1998) more recently analysed factors affecting consumer loan default. Since the early 1970s, major credit risk companies such as FairIsaac and Experian have invested large resources in developing models to predict loan default risk. Little of this work has been published, as the key information used is mostly proprietary.

A number of conceptual issues have been raised by the above studies of factors affecting loan repayment performance. Firstly, loan default studies need to clearly distinguish the type of borrower population for which factors affecting loan default are to be estimated. If the model intends to predict loan default of all "through the door" loan applicants, then a model that estimates this function based only on the accepted group of loan applicants will tend to give a downwardly-biased estimate of the probability of loan default (Reichert *et al.*, 1983; Boyes *et al.*, 1989; Greene, 1992). This implies that information about the rejected population must be included by conditioning the default model to account for a type of selection bias that results from only observing loan repayment for those borrowers that are accepted.

If the credit model intends to predict the loan default of existing borrowers, then it is of no consequence if the model is not conditioned for excluding the rejected sample population (Mortensen *et al.*, 1988; Boyes *et al.*, 1989). Credit models very often tend to focus only on predicting loan repayment performance over a single period debt contract. However, the credit decision is a multi-period decision over which the loan generates a flow of funds until the customer pays up the credit and decides not to take another loan, or defaults. During the life cycle of the customer, several loans may be taken before the customer pays up the credit and goes dormant. For a defaulting borrower, the time for which the loan is current is critical since the collection costs are high. If a loan is current for a sufficient period of time, it may be profitable to grant credit to a potentially defaulting customer (Eisenbeis, 1981).

Several credit models have accounted for the revenue maximizing credit decision by, for instance, adjusting the cut-off point in the classification tables of probability models for maximizing revenue rather than minimizing loan default (Mortensen *et al.*, 1988; Greene, 1992). This action has been justified since the pay-offs for correct and incorrect classification of borrowers are not equal. Roszbach (1998) modified the dependent variable in his credit model by assuming that 'time to default' would give an indication of the profitability of the loan contract. This assumption is rather limiting, since to obtain an accurate indication of the net revenue, the net present value of the cash flows resulting from the debt contract over time must be estimated. This requires accurate monthly cost data that are not always readily available.

It may not only be in a financial institution's interest to identify factors that affect loan repayment, but also to establish whether the loan granting decision process is effective (Boyes *et al.*, 1989; Hunte, 1993). This requires that the effectiveness of the characteristics that are used in the credit decision process must be validated against loan performance in order to establish whether the characteristics can predict loan default. Hunte (1993) and Boyes *et al.* (1989) developed credit models that tested the efficacy of the loan granting decision.

5.2 Objectives of the Analysis

Given the importance of the borrower screening process in the credit granting decision, the main objective of this analysis is to identify factors affecting the loan repayment performance of loans granted by two of the KZN MFOs discussed in Chapter 4, namely MFO1 and MFO2. As noted, MFO1 provides mainly consumption credit to low-income individuals that are formally employed, while MFO2 provides medium- and long-term agricultural finance to emerging small-scale farmers. Making the right credit decision has important consequences for lender viability and borrower investment choices. This is particularly pertinent for MFO1 which is operating in an increasingly competitive SA microfinance environment that requires balancing the right choices with a profit maximizing incentive. Given ready access to the data on consumption loan performance for MFO1, the analysis will evaluate the efficacy of MFO1's loan granting decisions. It will also condition the subsequent loan default model for MFO1 for the sampling bias that results from excluding the potential loan repayment performance of rejected loan applicants. Given the lack of detailed cost information for MFO1, the loan default model could not be extended to endogenously model the factors affecting loan performance, where the performance variable is based on borrower profit and not only on loan default. Identifying the factors that influence loan default can help MFO1 staff to refine the credit granting process. The results of this study may also assist staff to critically review the efficacy of the credit granting process to ensure that their credit decisions are based on information that matters.

The above analysis extends previous research on factors affecting loan default in the microfinance sector in several ways. Firstly, no previous work has been done in SA on identifying factors that affect loan default at a microfinance institution granting consumer loans. Secondly, no previous study in SA has been able to access information on rejected loans that can be used to validate the efficacy of the credit granting decision. This analysis also uses information provided by the credit bureau at the time of the loan assessment so that the role of this information can be assessed in the credit evaluation process *and* as a predictor of loan repayment performance. This is particularly important in the SA context where there the government is considering introducing a regulatory body to control credit bureaus and the information that they can provide to lenders to facilitate the loan granting decision. No international study on loan repayment performance at a microfinance institution has used this type of information to assess its potential influence on loan default. Section 5.3 below will derive the empirical models for the analysis of factors affecting the loan granting decision and loan repayment performance of consumption loans granted by MFO1.

5.3 Economic Model Specification for MFO1

Before specifying the economic model it is important to understand the credit screening technology used by MFO1. This lender operates in the mass credit market in SA and processes approximately 800 loan applications per day. The financial technology used by MFO1 restricts it to granting loans to individuals who are employed in the formal sector of the economy. To qualify for a loan, an applicant must be over 18 years of age, and produce a pay-slip and some form of identification. An application form is completed and captured onto the banking system. As MFO1 aims to disburse credit within one to two hours of the loan application being made, the credit vetting process must necessarily be fast and accurate. Only branch managers at MFO1 have the authority to approve or decline a loan.

The credit approval process relies on both the branch manager's local knowledge of individuals, and the assessment of information based on four broadly defined aspects of credit worthiness as determined by MFO1's policies and procedures. The four aspects are stability, contactability, affordability and previous credit history, and these aspects assess key areas of information that are required in order for the lending technology to operate. All loans are unsecured, with the only form of collateral being reputational capital, which is effected by the listing of delinquent borrowers by the credit bureau. Staff at MFO1 closely monitor the loan repayment performance of borrowers and start a process of telephonic follow-up (as soon as 5 days after an instalment is in arrears) backed up by a series of letters to encourage borrowers in arrears to repay.

With no collateral being taken, the credit assessment process is even more critical, since at this point a wrong decision may result in lost income opportunities if a potentially low-risk loan applicant is rationed out of the credit market. Conversely, if a potentially high-risk loan applicant is accepted, there may be increased costs due to additional monitoring and eventual loan write-off. Given that MFO1's objective is to maximize profits, the balance between accepting the right proportion of high- and low-risk loan applicants must be maintained.

Stability in relation to creditworthiness as defined by MFO1 has two aspects, namely the stability of income and the stability of residence for contactability purposes. Several proxy variables on MFO1's loan application form measure stability, such as the length of residence at the current residential address, time period of employment, age, and marital status. Given MFO1's financial technology, a borrower must be contactable for credit control purposes. A loan applicant's income must be stable, and the loan applicant must be able to repay the debt. Willingness to meet credit obligations is measured by the applicant's previous credit history as obtained from the credit bureau. Taking these factors, and any other knowledge of the loan applicant that the branch manager may have, into account will determine whether a loan is granted or not, and if a loan is granted, how much credit the loan applicant qualifies for. At the time of the study, the interest rate charged to borrowers was fixed, with no differentiation being made between high- and low-risk borrowers. In addition, MFO1 offered one standard term consumer loan of 4 months. Hence the only differentiation between high-and low-risk loan applicants was based on the loan amount.

The model of credit rationing and loan default for MFO1 used in this study is based on the theoretical frameworks derived by Stiglitz and Weiss (1981), Carter (1988), Hunte (1993) and Barham *et al.* (1996), and the empirical modeling framework used by Boyes *et al.* (1989), Greene (1992) and Jacobson and Roszbach (1998). The model assumptions are as follows:

1) Borrowers are heterogeneous, with different levels of credit risk, expected return and measurable probabilities of default. Lender MFO1 is thus assumed to ration loan applicants according to the perceived risks and probabilities of default. Although other terms and conditions of the loan contract such as interest rates and term should be varied according to credit risk, MFO1's financial technology at the time of the study did not permit this. Low-risk borrowers were thus necessarily subsidizing high-risk borrowers by virtue of paying the same interest rate.
2) Given borrower heterogeneity, MFO1 will undertake a rigorous screening process to differentiate its loan applicants into different credit risk classes. The only form of rationing that is observed is loan size rationing which ranges from being completely rationed (declined) to being partially rationed (the loan amount granted exceeds 0, but cannot exceed the loan amount that is requested).

3) Although the interest rate is set and is equally applied to all loans, the effect of the interest rate as a market clearing mechanism is reduced (Stiglitz and Weiss, 1981; Hoff and Stiglitz, 1990). However, the interest rate still has an adverse selection effect since some low-risk borrowers may consider that the rate is above their reservation price and may not consider applying for the credit. This leaves a potentially riskier pool of loan applicants.

4) The expected pay-off to MFO1 is given by:

$$
\begin{aligned}
E[\text{Income}] = \quad & (1 - P_D)(\text{finance charges} - \text{cost of capital}) \\
- \quad & P_D(\text{Bad debt} - \text{recovery amount} - \text{penalty interest}) \\
- \quad & \text{Fixed costs} \\
- \quad & (1 - P_D)(\text{Variable costs}) \\
- \quad & (P_D)(\text{Variable Costs}) \qquad (5.1)
\end{aligned}
$$

where P_D = the probability of loan default.

Equation (5.1) shows that as P_D decreases, the expected income of the lender increases and the loan applicant is less likely to be credit rationed. The increase in expected income results partly from the higher expected revenue and lower variable costs from assessing and monitoring the loan applicant. As P_D increases, the expected income decreases and the variable costs increase due to the additional monitoring of the loan applicant. Where P_D is sufficiently large such that $E[\text{Income}] \leq 0$, the loan applicant will be rationed fully and credit will not be granted.

The magnitude of P_D required to induce partial or full rationing depends on the size of the bad debt, the loan amount that is recovered, the potential income from penalty interest, and the structure of the fixed and variable costs (Hunte, 1993; Greene, 1992). For instance, if the recovery action is efficient, a higher level of bad debt can be carried, while the penalty interest may also defray some of the costs of default. It will also depend on the length of time for which the borrower is expected to remain current before defaulting (Eisenbeis, 1981; Roszbach, 1998).

The credit rationing decision is necessarily complex and depends on an interlinked set of costs, revenues and the expected default probability. However, a branch manager's assessment of the default probability is the key element that influences the rationing decision. Some risky borrowers may be accepted because the expected pay-off is greater than the expected costs. Hence it is critical to explore whether the decision made by the branch manager is effective in predicting P_D. In addition, the decision to grant credit will not necessarily only be based on the observable characteristics of loan applicants, but may also depend on unobservable characteristics as a result of the localized knowledge of the branch manager. The potential to earn revenue from a customer, if a potentially defaulting customer is current for a sufficient period of time (Eisenbeis, 1981; Boyes *et al.*, 1989; Greene, 1992; Roszbach, 1998), is also relevant.

To assess the factors that affect the credit rationing decision and loan repayment performance, the economic model for MFO1 will consist of two equations:

$$C_i = \beta_j v_{ji} + \varepsilon_i \qquad (5.2)$$

$$D_i = \alpha_j x_{ji} + \varpi_i \tag{5.3}$$

Equation (5.2) represents the credit rationing function and equation (5.3) represents the loan default function. The functions each have j parameter estimates (β, α) with j vectors of explanatory variables (v, x) for i loan applicants in Equation (5.2), and i borrowers in Equation (5.3). Variable C represents the latent, unobservable rationing ratio (number of loans accepted relative to total loan applications). The greater is C, the less the loan applicant is rationed, with C bound between 0 and 1.

Since MFO1 does not record the amount of credit requested, all that can be observed *ex post* is whether the sample applicant is granted credit, C = 1 (but the extent of the rationing is not known) or fully rationed, C = 0 (declined). Amemiya (1981), Maddala (1983), McFadden (1987) and Greene (2000) show that in this case the linear regression model can be extended to a binomial response by introducing an intermediate unobserved (latent) variable c^* such that:

$$\begin{gathered} c_i^* = \beta v_i + \varepsilon_i \\ \text{where} \\ C_i = z(c_i^*) = \begin{cases} 0 \text{ if } c^* = 0 \\ 1 \text{ if } c^* > 0 \end{cases} \end{gathered} \tag{5.4}$$

The objective of this study is to predict the probability that a sample loan applicant will be accepted, P_i as:

$$P_i = \text{Prob}[C_i = 1 | v_i] \tag{5.5}$$

If $F(\varepsilon | v)$ is the cumulative distribution function of the disturbances, then the probability that a sample loan applicant will be accepted is:

$$\begin{aligned}\mathrm{Prob}[C_i = 1 | v_i] &= \mathrm{Prob}[z(c_i^*) > 0 | v_i] \\ &= \mathrm{Prob}[\beta v_i + \varepsilon_i > 0] \\ &= F(\beta x_i | v_i]\end{aligned} \tag{5.6}$$

It is hypothesized that applicants who have more stable expected incomes, are contactable by telephone, can afford the debt and who have relatively fewer defaults with other lenders are more likely to be accepted by MFO1.

Variable D represents the latent unobserved propensity for an individual to default. The observed default arises from the defined vector of attributes (x) and random behaviour of borrowers. Loan default is assumed to occur in a single period that represents a specified duration of the customer relationship with MFO1 (Eisenbeis, 1981; Greene, 1992). The duration is based on the time period that it takes for the majority of new borrowers to become delinquent (Kindred, 2001b). This will be a fixed time period and, therefore, will not directly account for borrower profitability based on the duration of being current, since a true analysis of this sort requires detailed cost information that was not available for this study.

The greater is D, the higher is the propensity of the borrower to default. If D is relatively large enough, the borrower defaults on the loan. All that is observed *ex post* is whether the borrower defaults (Greene, 1992). Variable D can thus be represented by a latent unobservable variable d^* such that:

$$\begin{aligned}&d_i^* = \alpha x_i + \varpi_i \\ &\text{where} \\ &D_i = z(d_i^*) = \begin{cases} 0 \text{ if } d^* = 0 \\ 1 \text{ if } d^* > 0 \end{cases}\end{aligned} \tag{5.7}$$

The probability of default is obtained by:

$$\begin{aligned}\text{Prob}[D_i = 1 | x_i] &= \text{Prob}[z(d_i^*) > 0 | x_i] \\ &= \text{Prob}[\alpha x_i + \varpi_i > 0] \\ &= F(\alpha x_i | x_i]\end{aligned} \tag{5.8}$$

The vectors of attributes v_i and x_i (as captured by MFO1 on the loan application form) are based on the key aspects of MFO1's credit assessment process, namely: borrower stability, contactability, affordability, and credit history. Table 5.1 shows proxies for vectors v_i and x_i, and their expected effects on the probability of MFO1 applicants being granted credit.

5.3.1 Loan Applicant Stability

Proxy variables for stability include sample applicant age, length of residence at current address, length of employment at current employer, home ownership type, and economic activity. Older applicants tended to be married, were employed for longer, and had lower debt-to-income ratios. Age thus gives a relatively good indication of sample applicant stability and responsibility toward meeting debt commitments, as older applicants were more stable and less indebted than younger sample applicants. Vigano (1993) used age as a proxy for loan applicant stability and found that older borrowers had a better loan repayment record than younger borrowers. Boyes *et al.* (1989) found that older applicants had a greater likelihood of being accepted, and less likelihood of defaulting on their debt commitments. Greene (1992) and Aguilera-Alfred and Gonzalez-Vega (1993) also found that older borrowers were less likely to default. Older sample applicants are thus hypothesized to have a higher likelihood of being accepted and a lower likelihood of experiencing loan repayment problems.

Table 5.1 Definitions and Expected Signs for Variables used to Predict the Likelihood of being Granted Credit and of Loan Default for MFO1

Vectors of Explanatory Variables (v_i , x_i)	Expected sign for effect on granting credit (C = 1)	Expected sign for effect on loan default (D = 1)
Stability		
Age (years)	+	-
Gender (Male = 1, Female = 0)	-	+
Married (Married = 1, Other = 0)	+	-
Single (Single = 1, Other = 0)	-	+
Own Home (Yes = 1, No = 0)	+	-
Live with employer (Yes = 1, No = 0)	-	+
Live with parents (Yes = 1, No = 0)	-	+
Rent (Yes = 1, No = 0)	-	+
Location (Yes = 1, No = 0)	-/+	-/+
Home loan (Yes = 1, No = 0)	+	-
Bank account (Yes = 1, No = 0)	+	-
Length of residence at current address (months)	+	-
Employment sector (1 = Government, 0 = Private sector)	+/-	+/-
Number of months worked at current employer	+	-
Contactability		
Work telephone (Yes = 1, No = 0)	+	-
Home telephone (Yes = 1, No = 0)	+	-
Affordability		
Gross monthly income (Rand)	+	-
Net monthly income (Rand)	+	-
Monthly debt-to-net income ratio	+	-
Previous Credit History		
Average number of loans with other lenders at time of application	+	-
Total number of loans that were 2 – 3 months in arrears at time of application	-	+
Total number of loans that were 4 – 9 months in arrears at time of application	-	+
Total number of bad-debt write-offs at time of loan application	-	+
Branch effect		
Ladysmith	+	-
Pretoria	-	+
Pietermaritzburg	+	-

Loan applicants that are married are regarded as more stable as they tend to be settled at their place of residence. Given that married individuals have family responsibilities, they may also be less prone to changing employment. Single applicants are more likely to change accommodation and employment making it more difficult for MFO1 to track these clients. Boyes *et al.* (1989) found that married sample applicants had a greater likelihood of being accepted and were less likely to default. Loan applicants who are married are thus more likely to be granted credit and less likely to default, while single loan applicants are more likely to be credit rationed and more likely to experience loan repayment problems.

Loan applicants who own their homes are more likely to be contactable and have a stable income stream to maintain the home and potentially pay off the home loan should the property have a bond. Loan applicants that live with their parents or live on the property of their employer may not have sufficient income to afford to a home or to rent. Such individuals may also easily move to different premises and thus may be less contactable by MFO1 staff. Less contactable borrowers pose a greater credit risk, since contact by mail and telephone are important components of MFO1's lending technology. Similarly, loan applicants that rent accommodation may also be more prone to moving as a result of changing employment, increasing the risk of potential follow-up should the borrower default. Boyes *et al.* (1989) found that credit card loan applicants who owned their homes had a higher likelihood of being granted credit and a lower likelihood of defaulting on their loans, while applicants renting their accommodation had a higher likelihood of defaulting on their credit card debt. Loan applicants owning their homes are thus hypothesized to have a higher likelihood of being granted credit by MFO1 staff and a lower likelihood of loan default. Loan applicants that are living with their parents or on the employer's property or renting the accommodation are less likely to be granted a loan. Those who are granted a loan are more likely to experience loan repayment problems.

Loan applicants who have a home loan will have been subject to the rigorous screening criteria used by commercial banks that mostly deal with home mortgages. Individuals who have a home loan are also more likely to have higher income levels to be able to pay the debt. It is thus hypothesized that sample applicants who have a home loan are more likely to be granted credit by MFO1 staff and less likely to default. To open a bank account, applicants must have a certain minimum level of income. The presence of a bank account may also allow MFO1 to deduct loan repayments from the applicant's bank account by debit order, thus increasing the likelihood of loan repayment. A loan applicant with a bank account may thus more likely be granted credit by MFO1 staff and, given the potential for automatic loan payment deductions, be less likely to default on the loan.

The length of time lived at the current residential address, and the length of time worked at current employer, are also applicant stability proxies. These give some indication that contact by telephone or post is more likely, and that the applicant is relatively settled in a job with a lower likelihood of changing employment or possibly being retrenched. Boyes *et al.* (1989) found a positive relationship between the likelihood of loan acceptance and length of residence at current address and length of employment at current employer, and that borrowers who lived longer at their current address were less likely to default. Length of residence is thus hypothesized to be positively related to the probability of having a loan application accepted, and to be negatively related to the probability of loan default. Similarly, sample applicants that were employed for longer at their current employer may have a greater likelihood of being accepted and less likelihood of experiencing loan repayment problems.

Central to a credit contract is the promise to pay in future for cash received at the time that the credit contract is entered into - credit contracts are thus inherently risky (Hoff and Stiglitz, 1990; Barry *et al.*, 1995; Herath, 1996). To mitigate this risk, lenders must try to ensure that the loan applicant can service the future debt commitments. It matters, therefore, how the applicant derives the future income stream and whether the future income stream is stable or variable. Vigano (1993) found that applicants involved in economic sectors with less potential variability in income had a lower probability of default than those applicants involved in economic activities with more variable incomes.

Boyes *et al.* (1989) reported a statistically significant relationship between economic activity and the incidence of credit rationing - less skilled applicants earning lower incomes were rationed more than skilled applicants employed in managerial positions. Turvey (1991) and Schreiner (1999) also reported significant relationships between economic activity and incidence of client loan default. In this study the expected signs of the estimated coefficients for economic sector depend on what sectors the branch staff at MFO1 view as potentially more prone to income shocks, and which sectors actually are more prone. Hence the analysis of this variable will be exploratory in nature. Loan applicants deemed to be employed in sectors where the possibility of retrenchment or "short-time" is higher, are more likely to be credit rationed, while borrowers that are retrenched are less likely to repay their loans. Gender is also a potentially important discriminator, and if the past findings that women have a better repayment record than men in rural areas (Christen *et al.*, 1994; Schreiner, 1999) hold, then female loan applicants are more likely to be granted credit and less likely to default on their loans.

5.3.2 Loan Applicant Contactability

Two options available to the lender to try and ensure that borrowers have an incentive to repay debt over time are the use of collateral and the monitoring of the debt contract. Increasing the collateral requirements helps to solve the incentive problem, since the risk of non-compliance is shifted to the borrower (Barro 1976; Guttentag and Herring, 1984). Collateral is, however, seldom able to eliminate the incentive problem completely since borrowers may not be able to pledge collateral equal to the promised repayment amount. It is also costly to negotiate complete debt contracts, while realizing the full value of the collateral may not always be possible (Stiglitz and Weiss, 1981; Bester, 1985).

Hence where technology and cost allows, lenders also resort to monitoring the debt contract in order to restrict the opportunistic behaviour of borrowers. Increased monitoring results in lower opportunistic behaviour by borrowers, but comes at an increased cost (Navajas, 1999). Since MFO1 does not take collateral and is thus compelled to monitor debt contracts, the monitoring technology it uses must be cost-effective given the large number of borrowers that have to be tracked daily. Individual visits are too costly and hence telephones are used to contact borrowers that are in arrears. If borrowers are not contactable by telephone either at the work place or at home, the pay offs to monitoring are reduced, and there is likely to be an increase in the opportunistic behaviour of the borrowers. Potential borrowers that are contactable at work or at home are thus less likely to be credit rationed and are also less likely to default.

5.3.3 Loan Applicant Affordability

Barry *et al.*, (1995) define repayment capacity as the ability of borrowers to meet the full debt obligation from their surplus income. Okorie (1986), Boyes *et al.* (1989), Turvey (1991), and Miller and LaDue (1991) show that borrowers with lower debt-to-income ratios have less likelihood of defaulting on their debt commitments. Given the increased profile of borrower indebtedness within the regulatory framework of MFOs in South Africa that culminated in the formation of the NLR, it is particularly important that branch managers at MFO1 consider this information in the loan granting decision. Higher monthly debt-to-net income ratios for sample borrowers are thus likely to be positively associated with an increased probability of credit rationing and an increased probability of loan default.

5.3.4 Previous Credit History of the Loan Applicant

The expected stability of future income streams and the availability of income are important components in the credit assessment and loan default equations. A loan applicant may, however, have a relatively secure income and have sufficient funds to cover the additional debt, but may not be willing to meet the contractual obligations (Sanderatne, 1978). Willingness to meet contractual debt obligations can be assessed from the applicant's previous credit history as proxied by variables such as the number of delinquencies on other loan accounts and the number of bad debt write-offs.

Vigano (1993), Boyes *et al.* (1989) and Greene (1992) found that delinquencies on a loan applicant's previous loan(s) are positively related to increased levels of both credit rationing and loan default. Schreiner (1999) also reported that borrowers with more periods of arrears on previous loans had a higher likelihood of experiencing loan repayment problems. Loan applicant willingness to repay in the local study will be proxied by the number of previous loans with other lenders at the time of the loan application, number of payment profiles with mild arrears, number of payment profiles with major arrears, and number of bad debt write-offs. Branch managers at MFO1 critically assess these variables and tend to weight them heavily when assessing loan applications.

Loan applicants that had more previous loans with other lenders at the time of applying for a loan with MFO1 are expected to have more credit experience and hence be familiar with the potential implications of defaulting on a loan (e.g. being listed on a credit bureau). Loan applicants with previous loans may also have more experience in managing their debt. The credit bureau data is also likely to be more complete on these loan applicants, increasing the relevance of the bureau score, which makes it easier for branch managers to assess the credit risk. Schreiner (1999) found that borrowers with previous credit experience are less likely to default on the loans. Loan applicants at MFO1 with previous credit experience are thus less likely to be credit rationed and are also less likely to default on their debt with MFO1.

The number of payment profiles with minor and major arrears show MFO1 branch managers the sample applicant's attitude toward credit obligations. Although income shocks may contribute to poor loan repayment performance, persistent arrears with other lenders highlights the greater potential risk of granting credit to the loan applicant where the arrears may be linked not only to a poor attitude towards meeting contractual debt obligations, but also to higher indebtedness levels. A higher number of loans with other lenders that are in minor or major arrears may thus be positively related to increased levels of credit rationing and the increased likelihood of loan default. Similarly, the number of previous bad debt write-offs indicates the extent to which applicants have met their contractual debt obligations. Where this has happened in the past, applicants are at increased risk of not meeting their debt obligations again. The number of bad debt write-offs could thus be positively related to the increased likelihood of being credit rationed and the increased likelihood of loan default.

5.3.5 Effect of Branch Staff Differences

Since MFO1 has a decentralized credit granting system, the branch staff (and particularly the branch manager) has considerable authority in approving loans. Given the different levels of experience amongst branch managers and their different reactions to bonus incentive systems and training, some branch managers may make more risky decisions than others. Schreiner (1999) found that some branches grant loans to more risky borrowers than do other branches. Two of the MFO1 branch managers (Ladysmith and Pietermaritzburg) were relatively experienced, while the Pretoria branch manager had worked for MFO1 for less than one year. Hence it is expected that the Pretoria branch manager may be more conservative due to inexperience than the other two branch managers and hence ration loan applicants more. The quality of his credit decisions may also be relatively worse than those of the Pietermaritzburg and Ladysmith managers, and hence relatively more of the borrowers at the Pretoria branch are more likely to default.

5.4 Testing the Efficacy of the Loan Applicant Screening Mechanism of MFO1

To evaluate the efficacy of MFO1's loan applicant screening mechanism, the sign and level of statistical significance of the estimated β_j in equation (5.2) need to be compared to the sign and level of significance of the estimated α_j in equation (5.3). A statistically significant parameter estimate in equation (5.2) matched by a significant parameter estimate in equation (5.3) for the same variable indicates that MFO1 staff have correctly identified and used the information in assessing the credit worthiness of the loan applicant as this information is important in predicting the likelihood of loan repayment. A significant parameter estimate in equation (5.2) matched by a non-significant parameter estimate for the same variable in equation (5.3) will indicate that, while the information is regarded as useful in assessing the creditworthiness of the loan applicant, the information is not significant in predicting the probability of loan default. A statistically non-significant parameter estimate in equation (5.2) matched by a significant parameter estimate for the same variable in equation (5.3) indicates that MFO1 staff may have ignored potentially useful information in the screening process since this information is significant in predicting the likelihood of loan default but not significant in predicting the likelihood of being granted credit (Boyes *et al.*, 1989; Hunte 1993).

Given that equation (5.2) predicts the likelihood of a loan application being accepted and equation (5.3) the likelihood of an accepted loan applicant defaulting, a significant positive parameter estimate in equation (5.2) matched by a significant negative parameter estimate for the same variable in equation (5.3) indicates that the screening process was successful in identifying creditworthy loan applicants. This implies that a higher value for v_{ji} increases the likelihood of the loan applicant being accepted, while a higher value for the same variable x_{ji} decreases the likelihood of loan default.

A significant positive parameter estimate in equation (5.2) matched by a significant positive parameter estimate in equation (5.3) indicates that the screening mechanism was approving riskier loan applicants, since a higher value for v_{ji} increases the likelihood of being accepted while a higher value for the same x_{ji} increases the likelihood of default. A significant negative parameter estimate in equation (5.2) matched by a significant positive parameter estimate for the same variable in equation (5.3) indicates that MFO1 staff are successful in identifying default-prone borrowers correctly, and rationing them more strictly, since a higher value for v_{ji} increases the likelihood of being credit rationed while a higher value for the same x_{ji} increases the likelihood of loan default. Finally, a significant negative parameter estimate in equation (5.2) matched by a significant negative parameter estimate for the same variable in equation (5.3) indicates that the MFO1 staff are incorrectly rationing credit too strictly to creditworthy borrowers since a higher value for v_{ji} increases the likelihood of being credit rationed while a higher value for the same x_{ji} decreases the likelihood of loan default. The diagnostic matrix in Table 5.2 summarises the hypothesized efficacy of the screening mechanism.

Creditworthy borrowers are those in sector I and sector III in Table 5.2. Borrowers in sector III have been incorrectly rationed too strictly. This is a Type I error and may result in lost revenues for MFO1. Non-credit worthy borrowers are in sector II and sector IV. Borrowers in sector II have been incorrectly granted credit. This is a Type II error and results in increased costs for MFO1 as a result of the increased potential default (Hunte, 1993).

Table 5.2 Diagnostics for Evaluating the Efficacy of the Loan Applicant Screening Mechanism

Hypotheses	MFO1 Credit Action		MFO1 Credit Action	
	Ex ante	*Ex post*	*Ex ante*	*Ex post*
	No Rationing	Repayment	Rationing	Repayment
Creditworthy	$+\beta$	$-\alpha$	$-\beta$	$-\alpha$
	Sector I (No error)		Sector III (Type I error)	
Non-Creditworthy	$+\beta$	$+\alpha$	$-\beta$	$+\alpha$
	Sector II (Type II error)		Sector IV (No error)	

Source: Hunte, 1993: 74.

Incorrectly granting credit to a high-risk customer may be more costly, depending on the time taken to default and recovery rates and costs, and are the more serious of the two errors. Incorrectly rationing of a low-risk loan applicant still allows MFO1 to invest the funds in an alternative revenue-generating source such as an interest-bearing deposit account. Branch managers must, therefore, try to correctly assess the loan default probabilities of loan applicants.

5.5 The Sample Selection Problem for the MFO1 Loan Default Analysis

The loan applicant screening decision necessitates that branch managers at MFO1 try to predict the probability of loan default for all applicants. The empirical model used to estimate the probability of loan default must, therefore, apply to all "through the door" loan applicants, and not just loan applicants that have passed the initial screening and who have been granted credit (Reichert *et al.*, 1983; Boyes *et al.*, 1989; Greene, 1992). However, the only information that exists on loan default probabilities comes from sample applicants who were granted credit. The relevant issue is whether the default probabilities estimated using only information from accepted sample applicants would be the same as the default probabilities estimated for the sample applicant population as a whole. Consider equations (5.9) and (5.10):

$$\textbf{Credit Rationing equation:}\quad \begin{array}{l} C_i = \beta v_i + \varepsilon_i, \\ C_i = 1 \text{ iff } c_i^* > 0, \text{else } C_i = 0 \end{array} \tag{5.9}$$

$$\textbf{Default equation:}\quad \begin{array}{l} D_i = \alpha x_i + \varpi_i, \\ D_i = 1 \text{ iff } d_i^* > 0, \text{else } D_i = 0 \end{array} \tag{5.10}$$

Where

$$\begin{array}{l} D_i \text{ and } x_i \text{ are only observed if } C_i = 1, \\ C_i \text{ and } v_i \text{ are observed for all sample applicants} \end{array} \tag{5.11}$$

Since repayment behaviour is only observed for those sample applicants who were granted credit, Heckman (1979) shows that a type of incidental selection bias exists if the error terms in equation (5.9) and equation (5.10) are correlated. If the credit rationing decision is deterministically governed by sample applicant attributes, then the sample selection will not lead to biased parameter estimates in equation (5.9).

Eisenbeis (1978) argues that the credit granting decision may not only relate to the immediate loan but can be viewed as a multi-period decision that generates a flow of revenues over time that may extend beyond the term of the immediate loan. Determinants that are difficult to quantify, such as the branch manager's "gut feel", pressure to meet sales or loan recovery targets, and profit maximization, are thus important in the credit granting decision and may add an element of randomness that is captured in the error term of equation (5.10). Since the loan granting decision is not deterministically governed by loan applicant attributes, the error terms in equation (5.9) and (5.10) may be correlated, in which case there is a type of incidental selection. This results in biased parameter estimates in equation (5.9) if the default model is not conditioned specifically for this incidental selection as shown in equation (5.12):

$$\begin{aligned} E[D_i | D_i \text{ is observed}] &= E[d_i^* | c_i^* > 0] \\ &= E[d_i^* | \varepsilon_i > -\beta v_i \\ &= \alpha x_i + E[\varpi | \varepsilon_i > -\beta v_i] \\ &= \alpha x_i + \rho\sigma_\varpi \lambda_i(o_\varpi) \end{aligned} \tag{5.12}$$

where $o_u = -\beta v_i / \sigma_\varepsilon$ and $\lambda(o_\varepsilon) = \phi(\beta v_i / o_\varepsilon) / \Phi(\beta v_i / o_\varepsilon)$. Hence,

$$\begin{aligned} d_i^* | c_i^* > 0 &= E[d_i^* | c_i^* > 0] + \varpi_i \\ &= \alpha x_i + \rho\sigma_\varpi \lambda_i(o_\varepsilon) + \varpi_i \end{aligned} \tag{5.13}$$

The derivation of this model can be followed in Greene (2000). The term $\rho\sigma_\varpi \lambda_i(o_\varepsilon)$ results from the selection bias; ρ is the correlation between the error terms of equations (5.9) and (5.10), and λ represents the inverse of Mill's ratio. If the error terms in equations (5.9) and (5.10) were not correlated, the sample selection would be of no consequence, since the middle term in equation (5.12) would equate to 0.

However, given the correlation between the error terms, the consequence of ignoring the incidental sample selection is inconsistent parameter estimates. This would lead to an understatement of the true default probability if equation (5.9) were estimated without accounting for the middle term in equation (5.13) (Greene, 2000). This can be viewed as a problem of misspecification due to an omitted variable. An important underlying assumption of the bias specification in equation (5.13) is that the error terms in equations (5.9) and (5.10) follow a multivariate normal distribution (Heckman, 1979; Maddala, 1983; Greene, 2000). Although some doubt has been cast on the assumption, few of the alternative approaches can accommodate the breadth of models that the assumption of normality can achieve. The exploration of alternative approaches is still relatively new, with most of the empirical literature still being dominated by Heckman's (1979) model (Greene, 2000). The next section describes the sampling methodology used to collect data for the MFO1 econometric model.

5.6 Data Sampling for the MFO1 Econometric Model

To obtain information on the vectors of explanatory variables in equations (5.2) and (5.3), data on both accepted and rejected loan applications was obtained from MFO1. The data consisted of information captured on the loan application form, information obtained from the credit bureau inquiry that is done at the time of loan application, and loan performance information for those applicants that were granted a loan. The information captured on the application form and the bureau data constitute the application data used to identify characteristics that are correlated with events observed in the loan repayment performance data. In order to ensure that consistent data on the sample loan applicants were provided by MFO1, a detailed manual was developed by the author (see Appendix C) to specify each variable required for the analysis. This manual has since been adopted by MFO1 as guidelines to help staff in better defining information captured on its database, and has made subsequent analyses of loan applicant data easier and more consistent.

Data captured on the loan application form were obtained electronically for sample loan applicants. The credit bureau data were more problematic to collect. Two of the leading credit bureaus operating in SA were approached to provide data retrospectively on the sample loan applicants. Only one bureau could provide the data in a useable format, and took considerable time to return the data that consisted of loan applicant personal details, loan applicant inquiry history, payment-profile history (monthly repayment performance of loans with other lenders), and default and judgment history. Loan applicant bureau characteristics used in the empirical analysis were computed manually from the bureau data. This process was extremely time consuming and took about five months from when the data were received.

5.6.1 Application and Performance Windows

The period of time over which the application information is collected is the application window. This should ideally be a 12-month period to avoid the effects of seasonality that may be evident in the loan application information (PIC Solutions, 2000). However, other factors that influence the time period over which application data is observed are data availability, and the time needed for borrower repayment behaviour to mature (become good or bad). Prior to this study the time needed for an account to mature was not known. However, the MFO1 staff allowed a maximum of nine months before a delinquent account was handed over to the internal collection agency. Since handed-over accounts were never again considered for repeat business, this status was considered as the write-off status.

The data extraction process began in August 1999 and hence the final date on which loan performance was observed was set as 30 June 1999. Given the 9-month performance window, the final month in which characteristics of loan applicants could be observed was September 1998. The first month in which applications could be observed was February 1998, which is a 9-month application window. The shortened application window was due to MFO1 switching to a new banking system, which would for the first time make some of the information required for the study available electronically. Given the volumes of data, it was important that as much data as possible should be extracted electronically to simplify the data collection process. When the study commenced, only four of MFO1's 12 branches had been converted to the new banking system. Data from three branches, namely Ladysmith, Pretoria and Pietermaritzburg were used. Figure 5.1, summarises the time frames chosen for the application and performance window.

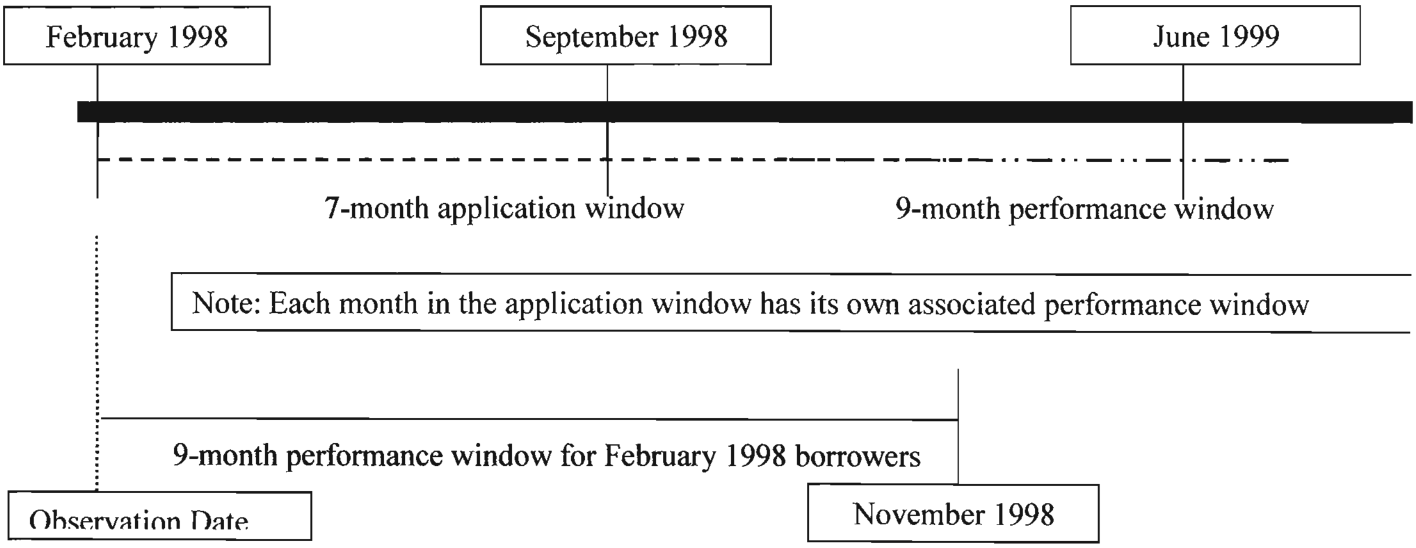

Figure 5.1 Diagrammatic representation of Application and Performance window

Based on previous studies by Mortensen *et al.* (1988), Boyes *et al.* (1989), Turvey (1991) and Aguilera-Alfred and Gonzalez-Vega (1993), loan performance for all sample borrowers would initially be observed at a single outcome date, namely 30 June 1999. This implied that sample borrowers that obtained their first loan earlier in the application window would have a longer performance period. Miller and LaDue (1991) and Greene (1992) specified a fixed period such that loan repayment performance for each sample borrower was observed over a 12-month period. This is preferable to observing performance at a fixed point in time as performance is observed over a consistent time period for each borrower (Kindred, 2001a). This approach, as shown in Figure 5.1, was used in this study to create consistency across sample borrowers.

5.6.2 Sampling Methodology Issues for MFO1 Data

Two methodological issues need to be accounted for when sampling data for models that estimate loan repayment probabilities. The first is that loan repayment behaviour is only observed for loan applicants that were granted a loan. Where the credit granting process is not deterministically governed by a set of loan applicant attributes, the absence of loan repayment performance for the rejected loan applicants is non-random (Heckman, 1979; Zmijewski, 1984; Boyes *et al.*, 1989). Parameter estimates of the model estimated with sample data only, for those loan applicants that were granted credit, may be downwardly biased since successful loan applicants, by nature of the prior selection, are less likely to default (Greene, 1992). For the estimated default model to be applicable to the "through the door" loan applicant population, it is important to condition the model on whether the loan applicant is accepted or rejected (Reichert *et al.,* 1983, Zmijewski, 1984, Miller and LaDue, 1991). If the intention is to estimate factors that influence the loan repayment performance of existing clients (a behavioural type loan performance model) then no sample selection problem exists. Since the objective of this study is to estimate the loan default probability of first-time loan applicants, the sample will include data from both accepted and rejected loan applicants.

Secondly, loan default rates reported in previous studies by Boyes *et al.* (1989), Miller and LaDue (1991), Greene (1992) and Schreiner (1999) were generally low (1% - 8% of loans). To obtain a more balanced sample for model estimation purposes, defaulting clients were over-sampled. This is a form of choice-based sampling, since the distinct population groups were identified first, where the probability of an observation entering the sample depends on whether the borrower is classified as good or bad. Choice-based sampling results in asymptotically biased parameter estimates, particularly where probability type estimation techniques are used (Zmijewski, 1984). To correct for this bias, Manski and Lermann (1977) derived the weighted endogenous sampling maximum likelihood (WESML) estimator. However, what the biased sampling does, the weighting undoes with the estimated parameters often exhibiting relatively large standard errors, which is what choice-based sampling attempts to avoid (Greene, 2000).

Lender MFO1 used a dynamic loan performance indicator where historic loan performance was not stored in the database. For this reason, choice-based sampling was not used since the performance groups were not clearly defined at the outset. The potential problem with this approach is that the number of observed defaults could be very low, creating instability in models using probability-type estimation techniques such as the probit or logit models. This instability is evident in large estimated standard errors for parameter estimates.

The study population was clearly separated into two strata: those loan applicants that were granted a loan and those that were rejected. These two strata were further stratified by branch - Pretoria, Ladysmith and Pietermaritzburg - to obtain accept and reject stratum per branch. To exploit the stratification of the target population into distinct groups where the sampling units are more homogeneous within each group, stratified random sampling was used to identify sample loan applicants (Barnett, 1992). Sampling each group independently by branch may result in sampling bias if the population proportions are not accounted for during the sampling process. To mitigate this bias, the strata were sampled by proportional allocation that accounts for the population proportions in the strata. This sampling process yields unbiased and efficient estimators of the population mean (Barnett, 1992). Sampling units from each stratum were drawn by a random sampling procedure.

Previous studies of consumer loan data have used large sample sizes to ensure that models are more robust. Boyes *et al.* (1989) had a sample of 4 632 loan applicants, while Greene (1992) used 13 444 observations, Schreiner (1999) had 39 956 cases, and Jacobson and Roszbach (1998) evaluated 13 338 loans. Credit card scoring literature, as a rule of thumb, suggests that the sample contains at least 1 500 good, 1 500 bad and 1 500 rejected customers. Each characteristic used in the analysis contains at least 50 observations per dependent variable category to ensure robustness of the characteristic (Kindred and Bailey, 2001).

To save costs and overcome limited resources to process the volumes of data, the researcher had to keep the total sample below these recommended sizes. Discussions with the MFO1 staff set the sample size at 800 loan applicants. Although this falls short of general accepted practices in loan default analysis, the main purpose of this study was not to build a predictive scoring system but rather to identify factors that influence the loan granting and loan default decision. The outcome of the stratified random sampling by proportional allocation is shown in Table 5.3.

The study population had a total of 5 257 loan applicants, from which 800 would be sampled. The sample size for each stratum was determined by proportional allocation so that the sample proportion of accepted and rejected loan applications are the same as for the population. Some sample accounts were not returned by MFO1 as they were identified as fraudulent applications. This resulted in a relatively small reduction of 7 accounts in the sample from 800 to 793. The biggest reduction in the sample came from accounts that were initially identified as rejects but which were loan applicants that were neither rejected nor accepted. These loan applicants were in a pending stage of the loan application where the branch manager required further information, or a guarantor. These loan applicants were not included in any of the analyses, as they had not reached a final decision stage in the loan application process.

Table 5.3 Population and Sample Distribution, 1998/ 1999

Branch	Pretoria	Ladysmith	Pietermaritzburg	Total
Accept	762	483	818	2 063
Reject	1 709	484	1 001	3 194
Total Study Population	2 471	967	1 819	5 257
Sample Size	800			
Sample Accept	116	74	124	314
Sample Reject	260	74	152	486
Total	376	147	277	800
Accepts for which data was received	115	74	122	311
Rejects for which data was received	260	73	150	483
Total received	375	146	272	793
Total useable accepts	113	73	122	308
Total useable rejects	228	57	133	418
Total useable sampling units	341	130	255	726
Accepts not useable	2	1	0	3
Rejects not useable	31	17	17	65

The Pretoria branch with the highest loan applicant population was sampled the most. Ladysmith represented the smallest number of sampling units in the frame (see Figure 5.2 below).

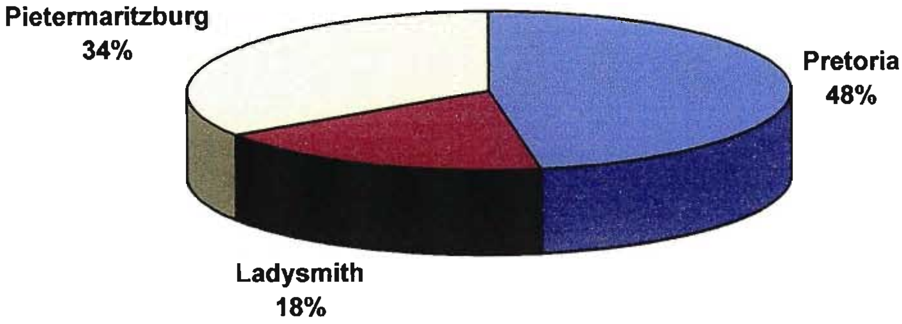

Figure 5.2 Sample Distribution by MFO1 Branch

Table 5.4 shows that as a result of the exclusions, the sample distribution shifted in favour of the accepted loan applications (accepts). The Ladysmith branch had the biggest shift in sample distribution toward the accepted loans category. The exclusions indicate the extent to which the branch manager's ability to make a decision is slowed by factors such as a lack of information or a lack of experience. Information problems may have been more prevalent at the rural Ladysmith branch, while the lack of experience of the newly appointed branch manager at Pretoria could have resulted in relatively high pending or waiting status of loans.

The relatively lower approval rate of 30.8% at the Pretoria branch further shows the manager's lack of experience, as confirmed by staff at MFO1's head office. The Ladysmith and Pietermaritzburg branches had relatively high approval rates of 49.1% and 44.69%, respectively. This is evidence of more experienced branch managers, and perhaps a less risky pool of loan applicants, even though loan applicants would potentially have to wait longer for loan approval.

Table 5.4 Distributions of Accepted and Rejected Loan Applicants, 1998/ 1999

Branch	Pretoria	Ladysmith	Pietermaritzburg	Total
Accept	30.8%	49.1%	44.9%	39.2%
Reject	69.1%	50.1%	55.1%	60.8%
Total Study Population	100.0%	100.0%	100.0%	100.0%
Sample as % of Population	15.2%	15.2%	15.2%	15.2%
Total useable accepts	33.1%	56.2%	47.8%	42.4%
Total useable rejects	66.9%	43.8%	52.2%	57.6%
Total useable sample	100.0%	100.0%	100.0%	100.0%
Exclusions as a % of sample received	8.8%	12.3%	6.3%	8.6%

5.6.3 Definition of Loan Repayment Performance

Central to any analysis of the factors affecting loan repayment is the delinquency definition. Past studies have used different delinquency definitions: Sanderatne (1978), Boakye-Dankwa (1979) and Okori (1986) relied on loan recovery rates or proportion of balances in arrears as repayment performance indicators. Boyes *et al.* (1989), Turvey (1991), Vigano (1993) and Jacobson and Roszbach (1998) based loan performance on the financial institution's definition of 'good' and 'bad' clients, and are not explicit to how these are defined. Dietrich and Kaplan (1982) relied on the subjective classification of borrowers by loan officers into different loan repayment performance categories. Reinke (1998) defined loan repayment performance between borrowers that are in good standing and borrowers that are not. Mortensen *et al.* (1988) defined a borrower as non-current if any portion of the principal or interest due at the performance observation date is in arrears. Lugemwa and Darroch (1995) classified a borrower as delinquent if the entire loan was not repaid.

Greene's (1992) analysis of the performance of credit card customers defined them as bad after having skipped payment for six months in a 12-month period. Aguilera Alfred and Gonzalez-Vega (1993) classified a borrower as good if the installment was paid within 30 days of the due date, in arrears if the installment was paid 30 days after the installment due date, and in default if the installments remained unpaid 30 days after the due date. Schreiner (1999) defined a borrower as delinquent if the borrower had a spell of arrears of at least 15 days. The above definitions of 'good' and 'bad' borrowers tend to be study-specific and depend on the way in which study lenders structure and record loan repayment, and the objectives of the analysis.

Kindred (2001a) provides a guideline to loan performance definitions for empirical analysis of loan repayment. A borrower should be considered 'bad' if the lender refused to grant further credit at that delinquency level, or the lender would not have granted credit in the knowledge that the borrower would have gone delinquent. Similarly, a customer should be considered 'good', if based on the performance of the account, the lender would want to grant credit or continue to grant credit to the customer. Furthermore, Miller and LaDue (1991) emphasised the need for an objective repayment performance definition based on observable repayment performance.

The repayment performance definition used in this study for MFO1 was based on the observed repayment performance of sample borrowers. Several methodological issues arose in the computation of the arrears indicator. Since MFO1 provided short-term, 4-month consumption loans that were on average repaid in less than four months, repayment performance could not necessarily be based on the first loan, since customer behaviour patterns would not have stabilized. Loan repayment performance thus had to be measured over a longer period of time and over several loans, with the 9-month performance window providing the guideline. The existing loan ageing practice of MFO1 also stopped once the loan was handed over to the internal collection agency. Hence, arrears monitoring was not possible from this point. Historic loan repayment performance was also not stored in the database, which meant that loan repayment performance would have to be recalculated.

Given that loans to MFO1 clients are repayable in monthly installments, the loan performance calculation was based on a common consumer loans industry delinquency indicator known as the contractual delinquency or CD (PIC Solutions, 2000). The CD estimates the portion of the installment that is in arrears while the loan is in term, and adds the number of months that the loan is past the final payment date when the loan is out of term. Since MFO1 capitalized the interest charged for the loan up-front, the CD was computed as follows:

CD = (Capital + interest in arrears)/monthly installment due (+ 1 for every month that the loan remains unpaid when out of term). (5.14)

This indicator was calculated for each loan granted to the sample borrowers. Where sample borrowers had concurrent loans, CD was calculated for each loan based on the payment hierarchy rules used by MFO1 that are shown in Figure 5.3.

Interest overdue on the oldest loan was settled first, followed by interest overdue on the most recent loan. If there are sufficient funds left from the payment, the portion of capital and finance charges in arrears on the oldest loan are settled, followed by capital and finance charges in arrears on the most recent loan. Finally, the current installments are settled if the payment made by the borrower was large enough. As MFO1 only had printed transaction lists of the customers' loan history, each installment and payment had to be captured manually to compute CD. To ensure that all the relevant information to compute CD was captured, a data capture form (see Appendix D) was used. This information was transferred to an Excel spreadsheet for computation of contractual delinquency for 308 borrowers (and over 1 000 loans), where each loan was classified as being one of CD0 ($0 \leq CD < 1$), CD1 ($1 \leq CD < 2$), CD2 ($2 \leq CD < 3$) and CD3+ ($3 \leq CD < \infty$).

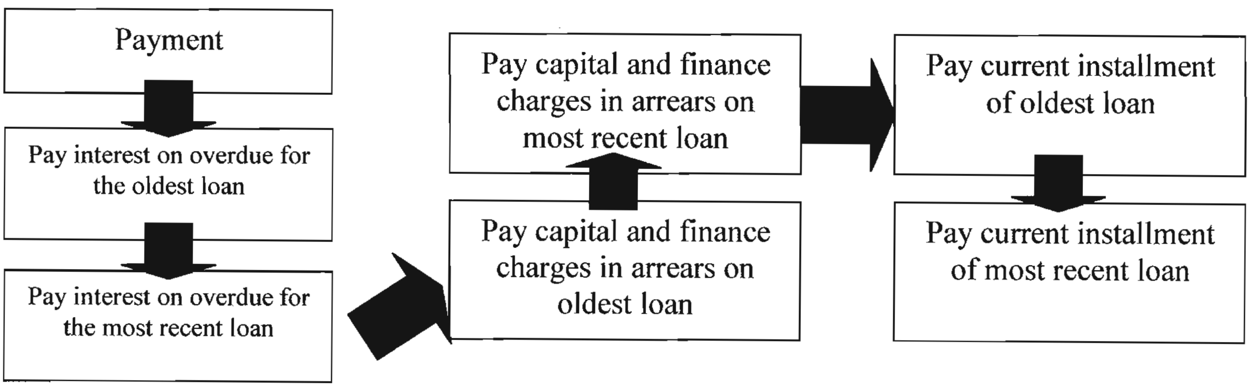

Figure 5.3 Payment hierarchy used by MFO1

Previous studies on factors affecting loan default were mostly at customer level, although much mention is made of loan default. Borrowers in these studies only tended to have one loan or one credit facility in the case of consumer loans (Boyes *at al.*, 1989; Greene, 1992). Since one customer can have many loans at MFO1, and the objective of this study is to analyse customer rather than loan characteristics, a default indicator at customer level is derived from the performance of individual loans. For this it was important to determine how many loans each customer had on average in the 9-month performance window, as shown in Table 5.5.

Table 5.5 Number of Loans in the 9-month Performance Window for MFO1, 1998/1999

Application Month	Number of loans			
	1	2	3	4+
January 1998	18	17	15	0
February 1998	28	22	16	0
March 1998	35	27	22	0
April 1998	55	50	33	0
May 1998	33	24	21	0
June 1998	37	32	26	0
July 1998	42	35	27	0
August 1998	44	40	28	0
September 1998	16	15	7	0

Of the borrowers that were granted their first loan in January 1998, 18 had one loan in the 9-month performance window, while 15 of the 18 had three loans. This trend emerges throughout the application months. A combined loan repayment performance indicator per borrower was thus based on the performance of, at most, the first three loans per customer. Satisfactory or 'good' borrowers were defined as clients for whom any of the first three loans did not age past CD1. 'Bad' customers were defined as clients for whom any of the first three loans reached CD2 or greater.

Table 5.6 gives the distribution of good and bad borrowers for the three MFO1 branches. Most of the sample borrowers were current (75.9%), while 24.1% were in arrears. The Pietermaritzburg branch had the lowest level of delinquency and the Pretoria branch the highest. Credit scoring models will usually omit a class of borrower performance known as 'indeterminates' that are not considered 'good' or 'bad' (Kindred, 2001a). These are normally customers with loan performance like CD2. As the objective of this study is not to build a scoring model but to broadly identify factors that influence borrower repayment performance, the indeterminates were not omitted from this study, but were rather included as 'bad ' borrowers.

Table 5.6 Distribution of Good and Bad Sample Borrowers, 1998/ 1999

	Total	Good Borrowers		Bad Borrowers	
	n	n	%	n	%
Ladysmith	73	53	72.6	20	27.4
Pretoria	113	78	69.0	35	31.0
Pietermaritzburg	122	103	84.4	19	15.6
Total	308	234	75.9	74	24.1

There was a statistically significant difference between the mean average 'bad' rate for the Ladysmith and Pietermaritzburg branches, and for the Pretoria and Pietermaritzburg branches at the 5% and 1% levels of significance, respectively. The Ladysmith branch had the highest acceptance rate but also a relatively high default rate (not as high as the Pretoria branch). The Pietermaritzburg branch, although having a fairly high acceptance rate of 44%, had the lowest default rate. The Pretoria branch with the lowest acceptance rate of 30% had the highest default rate. The branch manager at Ladysmith had the most experience and, therefore, seemed willing to accept some potential credit risks in order to try and achieve the required branch profit targets. The Pretoria branch manager had the least credit granting experience (less than one year), and, therefore, was more conservative in granting credit but not necessarily making the right credit granting decisions given the high bad debt rate. Section 5.6.4 presents some key descriptive characteristics of the sample data obtained from MFO1 and the empirical models of credit rationing and loan repayment performance for MFO1 clients.

5.6.4 Descriptive Characteristics of Factors Affecting MFO1 Loan Granting Decisions

The decision by MFO1 loan officers to accept or reject a loan applicant is based on client stability, contactability, affordability and credit history. Stability is represented by age, marital status, length of residence at current address, length of employment at current employer, and type of employer. Contactability is proxied by being able to make telephone contact at home or at work or both. Affordability is reflected by the loan applicant's gross and, more importantly, net income (as shown on the payslip – normally gross income less insurance, tax, and medical aid deductions). Credit history is based on the information received from the credit bureau on the loan applicant's loan repayment history with other lenders. The importance of these factors in driving the credit granting decision and guiding the credit rationing behaviour of loan officers will be considered in this section.

5.6.4.1 Descriptive Characteristics of Loan Applicants for the Ladysmith Branch

Table 5.7 shows that applicants that were accepted were, on average, older than rejected applicants (37 years versus 34 years). This difference was statistically significant at the 5% level of significance. On average, Ladysmith branch staff accepted more male loan applicants, although the difference in means is not statistically significant. Male loan applicants tended to be more credit active and higher income earners, which meant that the bureau data obtained for these clients had more information to base the decision on. Regarding martial status, Table 5.7 shows that there was a statistically significant difference between single applicants that were accepted and those that were rejected. Single sample applicants were considered less stable by

Ladysmith branch staff as single applicants were generally younger, and less settled at their place of employment (and were more difficult to contact) (the default category for marital status included both divorced and widowed applicants)

Table 5.7 Comparison of Means for Accepted and Rejected Loan Applicants for the Ladysmith Branch of MFO1, 1998/ 1999

Characteristic	Reject		Accept		t- value
	n	Mean	n	Mean	
Age (years)	54	34.0	73	37.1	1.856*
Gender (Male = 1, Female = 0)	56	0.57	73	0.60	0.356
Married (Married = 1, 0 = Other)	55	0.38	73	0.51	1.407
Single (Single = 1, 0 = Other)	55	0.60	73	0.40	-2.301**
Own Home (Yes = 1, No = 0)	55	0.42	73	0.48	0.685
Live with employer (Yes = 1, No = 0)	55	0.05	73	0.03	-0.781
Live with parents (Yes = 1, No = 0)	55	0.29	73	0.23	-0.739
Rent (Yes = 1, No = 0)	55	0.11	73	0.10	-0.243
Location (Yes = 1, No = 0)	53	0.09	70	0.13	0.588
Home Loan (Yes = 1, No = 0)	55	0.07	73	0.14	1.150
Bank Account (Yes = 1, No = 0)	55	1.73	73	1.88	1.968*
Length of Residence at current address (months)	55	181.18	73	171.93	-0.344
Employment Sector (1 = Government, 0 = Private Sector)	55	0.49	73	0.51	0.177
Number of months worked at current employer	55	77.13	73	97.67	1.445
Work telephone (Yes = 1, No = 0)	55	0.91	73	0.84	-1.120
Home telephone (Yes = 1, No = 0)	55	0.35	73	0.51	1.832*
Gross monthly income (Rand)	55	R2 365	73	R2 788	1.661**
Net monthly income (Rand)	55	R1 548	73	R1 964	2.853***
Monthly debt-to-net income ratio	55	0.18	73	0.12	-2.121***
Average number of loans with other lenders at time of application	54	2.43	73	1.90	-1.944**
Total number of loans that were 2 – 3 months in arrears at time of application	54	0.31	73	0.14	-2.161**
Total number of loans that were 4 – 9 months in arrears at time of application	54	0.33	73	0.01	-4.569***
Total number of bad-debt write-offs at time of loan application	57	0.63	73	0.07	-4.736***

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels of significance, respectively.

Loan applicants that owned their home or lived in a location were more readily accepted by Ladysmith branch staff than applicants who lived on the premises of their employer, lived with parents or rented their accommodation. While applicants that owned their homes are regarded as more stable, it should also be noted that a large proportion of the Ladysmith low-income population lives in locations (previously demarcated areas for black settlements). Although applications living in locations do not own their property, they can be regarded as relatively stable, as few households will move from their allocated plot in the location.

There may also be a degree of 'noise' that may have reduced the information provided by this variable. For instance, some applicants that live in locations may have indicated that they own their homes. Applicants living with their parents or renting accommodation may be regarded as less stable as they are more likely to move and, therefore, may be perceived as less contactable. There was no statistically significant difference between accepted and rejected Ladysmith applicants in terms of home type. Although there was a statistically significant difference between accept and reject rates, Ladysmith branch staff more readily accepted loan applicants that had a home loan. Having a home loan implies a degree of creditworthiness, since the loan applicant would have had to pass the stringent credit assessments of commercial banks that usually granted home loans. On average, more accepted Ladysmith applicants had bank accounts than rejected applicants. Although banking details do not usually form part of the MFO1 branch staff's credit assessment, applicants with bank accounts had, on average, a higher gross monthly income than applicants without a bank account.

Table 5.7 shows that rejected applicants at the Ladysmith branch had been at the current address for a longer period than accepted loan applicants, but this difference (181 versus 172) was not statistically significant. As this is a common credit-scoring variable, sample applicants often overstate this period, which introduces inconsistencies into this information. The applicant's employment sector may indicate the potential stability of future expected income streams that are important for securing debt repayments. Ladysmith branch staff accepted more applicants employed in the government sector. Their income streams may be more secure as the likelihood of bankruptcy or dismissal may be relatively low compared to MFO1 applicants employed in the private sector. There was no statistically significant difference between the accepted and rejected applicants at this branch in terms of employment sector.

A further indicator of employment stability is the length of time that applicants had worked for their employer. On average, accepted Ladysmith applicants were employed for longer (98 months versus 77 months), but there was no statistically significant difference in employment period between the two groups of applicants. Staff at MFO1 attached no physical collateral to secure the credit granted, and hence relied on close monitoring of applicants during the loan repayment cycle to try and ensure repayment. This monitoring was effected mostly through immediate telephonic follow-up should the customer not repay the monthly installment on time. Hence it was important when applying for loans that the applicants could provide a home and/or a work telephone number. Table 5.7 shows that, on average, Ladysmith branch staff accepted more loan applicants that had a home telephone number, with the difference being statistically significant. Most of the Ladysmith applicants were either teachers in remote rural areas or factory workers. As it was difficult to contact these two groups at work, this source of contact was less important for the branch staff.

Loan applicant ability to repay the loan is an important consideration in the assessment of creditworthiness. A loan applicant may be willing to repay the debt, but unable to repay if available income cannot cover the debt commitments. Accepted Ladysmith applicants had statistically significantly higher average net and gross monthly incomes compared to rejected applicants (R1 964 and R2 788 versus R2 365 and R1 548, respectively). The existing debt of the sample applicants relative to available income is also a key factor in assessing the potential for the applicants to incur more debt. Branch managers at MFO1 do critically review existing debt commitments, relative to net income, at the time of the loan application. A relatively high debt-to-income ratio may increase the financial pressure on the sample applicant and reduce the ability to repay. This study uses the ratio of retail debt commitments-to-net monthly income to assess client debt loading. The ratio takes into account any debt commitments that are part of the applicant's salary deductions, tax and insurance obligations, in the denominator. Additional debt commitments that are not part of the salary deductions are accounted for in the numerator and consist of retail debt commitments as indicated by the credit bureau. The retail debt-to-income ratio was statistically significantly different for accepted and rejected Ladysmith applicants. Accepted applicants had a mean debt-to-income ratio of 12%, while rejected applicants had a mean ratio of 18%.

Rejected sample applicants, on average, have statistically significantly more previous loans with other lenders. *A priori*, it is expected that the more loans a sample applicant has or has had with other lenders, the more established is the credit history, and the potentially more creditworthy is the applicant. If these loans are active, however, the incidence of credit rationing may be higher because of higher debt commitments. In addition, sample applicants with more loans with other lenders are more likely to have experienced loan repayment problems at some stage in time.

Payment profile information is probably the credit bureau information that is most scrutinized by MFO1 staff. Discussions with branch managers at MFO1 indicate that this information, together with bad debt write-offs, carries the most weight in the decision on whether or not to grant credit. Whether the payment profile and bad debt information at the credit bureau is consistent and always correct is debatable. The author identified numerous inconsistencies in the payment profile information when gathering the credit bureau information. These ranged from questionable arrears definitions to inconsistent and incorrect information. Although most credit grantors that provide information to the credit bureau used in this study belong to a collective body, whose function is partly to control the quality of information that is submitted, there seems to be very little uniformity in arrears definitions and consistency with which data is supplied to the bureau. This is understandable, given that furniture and clothing retailers have different credit models with different payment tolerance levels.

When this information is used to make credit granting decisions and to build bureau scorecards, it is imperative that there be consistency in the data. Clothing retailers, for example, may regard a payment of 60% - 70% of an installment as current, whereas MFO1 has no tolerance level and staff will regard an installment as in arrears one day past its due date. These issues need to be considered when using payment profile information. This study divides the payment profile information into two categories, namely profiles that have not had arrears worse than three months in the six months leading up to the loan application with MFO1, and profiles with arrears of more than three months in the six months leading up to the application. Table 5.7 shows that, on average, most Ladysmith applicants with minor (not worse than three months) and major payment profile arrears (more than three months) were rejected by branch staff (0.31 and 0.33 versus 0.14 and 0.01, respectively). The differences in means were statistically significant at the 1% level of significance. Given the emphasis on payment profile information, it is imperative that such data are displayed correctly and interpreted correctly. Here the responsibility lies with both the providers of the information *and* credit bureau staff. Providers must submit 'clean' information timeously to the credit bureau, and credit bureau staff should ensure that the data are presented consistently to credit providers who need it. Most of the Ladysmith applicants that had a default listing at the credit bureau were rejected. The difference in mean default listings between the applicant groups was statistically significant, suggesting that this is a key factor that branch managers consider when reviewing the credit application for approval. The period since default did not seem to matter for the branch managers. This may be a questionable practice since defaults that are older than 18-24 months may not be that relevant. If an individual defaults on credit obligations, however, the likelihood that this will happen again may be very high.

5.6.4.2 Descriptive Characteristics of Loan Applicants for the Pretoria Branch

Table 5.8 shows that applicants that were accepted by Pretoria staff are, on average, older than rejected sample applicants (36.4 years versus 35.7 years), but this difference was not statistically significant (contrary to the age difference at the Ladysmith branch). The Pretoria branch staff rejected a higher proportion of female sample applicants who tended to have higher debt-to-income ratios and relatively poor credit histories with other lenders. The difference in means was statistically significant at the 5% level of significance. Similarly to Ladysmith staff, Pretoria staff accepted more applicants that were married and fewer that were single, as married applicants were considered more stable (older and more settled at their place of employment), although the difference in means was not statistically significant. There was also no significant difference between accepted and rejected Pretoria applicants according to home ownership type. Similar to the Ladysmith staff choices, Pretoria staff tended to accept applicants who owned their homes rather than those who rented accommodation, lived with their employer or lived with their parents (were less contactable).

Although, on average, fewer Pretoria applicants had a home loan, more applicants had a bank account compared to the Ladysmith applicants. Table 5.8 shows that the difference in means was not statistically significant, which is consistent with *a priori* expectations, as branch staff do not use this information in the screening process. Accepted Pretoria applicants had lived, on average, longer at their current home address than rejected applicants (174 months versus 147 months). This difference in length of stay was statistically significant at the 10% level of significance. This result is different to that of Ladysmith where rejected applicants tended to have lived for longer at their current home address.

There was no statistically significant difference between accepted and rejected applicants in terms of employment sector at Pretoria, even though, similar to Ladysmith, Pretoria staff accepted, on average, more applicants employed in the government sector. Both accepted and rejected Pretoria applicants had worked for a similar period of time at their employer when applying for credit at MFO1 (87.7 months versus 86.7 months) while there was a marked, although not statistically significant, difference at the Ladysmith branch.

Table 5.8 Comparison of Means between Accepted and Rejected Loan Applicants for the Pretoria Branch of MFO1, 1998/ 1999

Characteristic	Reject		Accept		t- value
	n	Mean	n	Mean	
Age (years)	206	35.70	113	36.42	0.705
Gender (Male = 1, 0 = Female)	228	0.53	113	0.64	1.948**
Married (Married = 1, 0 = Other)	228	0.49	113	0.52	0.612
Single (Single = 1, 0 = Other)	228	0.43	113	0.38	-0.945
Own Home (Yes = 1, No = 0)	228	0.47	113	0.51	0.687
Live with employer (Yes = 1, No = 0)	228	0.09	113	0.02	0.719
Live with parents (Yes = 1, No = 0)	228	0.29	113	0.32	0.551
Rent (Yes = 1, No = 0)	228	0.15	113	0.14	-0.184
Location (Yes = 1, No = 0)	212	0.01	113	0.09	-0.052
Home Loan (Yes = 1, No = 0)	228	0.21	113	0.19	-0.432
Bank Account (Yes = 1, No = 0)	194	1.98	113	2.00	1.316
Length of Residence at cur address (months)	228	147.13	113	173.88	1.612*
Employment Sector (1 = Government, 0 = Private Sector)	216	1.48	113	1.52	0.778
Number of months worked at current employer	216	86.71	113	87.73	0.119
Work telephone (Yes = 1, No = 0)	216	0.98	113	0.99	0.679
Home telephone (Yes = 1, No = 0)	228	0.43	113	0.56	2.233**
Gross monthly income (Rand)	216	2 713.61	113	3 070.68	0.076
Net monthly income (Rand)	216	1 677.79	113	2 045.88	0.011***
Monthly debt-to-net income ratio	186	0.25	112	0.13	-2.834***
Average no. of loans with other lenders at time of application	203	2.66	107	2.27	-2.310**
Total number of loans that were 2 – 3 months in arrears at time of application	203	0.55	107	0.13	-5.146***
Total number of loans that were 4 – 9 months in arrears at time of application	203	0.43	107	0.02	-6.092***
Total number of bad-debt write-offs at time of loan application	228	0.63	113	0.18	-4.721***

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels, respectively.

Table 5.8 shows that, on average, both accepted and rejected applicants were readily contactable at their place of employment, while fewer rejected applicants were contactable by telephone at home than accepted applicants. The difference in means between accepted and rejected sample applicants was statistically significant at the 5% level of significance. Even though most Pretoria applicants had access to a work telephone, it was important for Pretoria staff to be able to contact borrowers at home since telephonic contact at work was not always reliable. Similar to Ladysmith applicants, accepted Pretoria loan applicants had statistically significantly higher average gross and net monthly incomes compared to rejected applicants (R3 071 and R2 045 versus R2 714 and R1 678, respectively). The average incomes were also higher than those of Ladysmith applicants, indicating the higher earnings potential in the more urban and developed cities of SA (particularly Pretoria and Johannesburg which are the industrial hubs of SA).

Table 5.8 shows that Pretoria branch staff also paid considerable attention to the loan applicant's debt-to-income ratio. Rejected applicants had a mean debt-to-income ratio of 25% versus 13% for accepted applicants, the difference in means being statistically significant at the 1% level of significance. Compared to Ladysmith accepted applicants, the Pretoria accepted borrowers had relatively higher mean debt-to-income ratios.

Pretoria applicants were, on average, more credit active than applicants at the Ladysmith branch. Accepted applicants had a mean of 2.27 loans with other lenders at the time of application, while rejected applicants had a mean of 2.66 loans (versus 1.90 and 2.43, respectively, for Ladysmith applicants). Again, the incidence of credit rationing was higher because most of these loans were active at the time of loan application. The difference was statistically significant. Similar to

Ladysmith staff, Pretoria staff relied heavily on payment profile information provided by the credit bureau in their assessment of credit worthiness. Rejected applicants had more payment profiles with mild and serious arrears than did accepted applicants. Given the increased level of credit activity by Pretoria applicants, they had a higher incidence of payment profile arrears than Ladysmith applicants. On average, rejected Pretoria applicants also tended to have statistically significantly more bad-debt write-offs than did accepted applicants.

5.6.4.3 Descriptive Characteristics of Loan Applicants for the Pietermaritzburg Branch

Similar to both Ladysmith and Pretoria, Table 5.9 shows that applicants that were accepted were, on average, older than rejected applicants (36 years versus 34 years), but this difference was not statistically significant. Contrary to the Pretoria and Ladysmith branches, Pietermaritzburg branch staff, on average, accepted a statistically significantly higher proportion of female sample applicants. These applicants tended to have better credit track records with other lenders and lower levels of indebtedness relative to rejected female and male sample applicants. Regarding marital status, Pietermaritzburg staff accepted, on average, more married applicants and fewer single applicants, but the differences in means were not statistically significant.

Home ownership type was not a key factor in the credit-granting decision process for Pietermaritzburg staff. On average, a greater proportion of accepted applicants owned their home, than lived with their parents or on the employer's premises, rented or lived in the nearby location. There is no clear trend as to what home ownership type was considered important by branch staff. There was a statistically significant difference between accept and reject applicants in terms of whether or not they had home loans. Having a home loan implies a degree of creditworthiness, since the loan applicants would have had to pass the stringent credit assessments of the commercial banks.

Table 5.9 Comparison of Means between Accepted and Rejected Loan Applicants for the Pietermaritzburg Branch of MFO1, 1998/ 1999

Characteristic	Reject		Accept		t- value
	n	Mean	N	Mean	
Age (years)	131	34.31	122	36.05	1.452
Gender (Male = 1, Female = 0)	133	0.71	122	0.59	-1.958**
Married (Married = 1, Other = 0)	133	0.42	122	0.48	1.001
Single (Single = 1, Other = 0)	133	0.56	122	0.47	-1.545
Own Home (Yes = 1, No = 0)	133	0.16	122	0.22	1.293
Live with employer (Yes = 1, No = 0)	133	0.03	122	0.06	1.070
Live with parents (Yes = 1, No = 0)	133	0.29	122	0.25	-0.848
Rent (Yes = 1, No = 0)	133	0.22	122	0.18	-0.750
Location (Yes = 1, No = 0)	132	0.29	122	0.29	-0.006
Home Loan (Yes = 1, No = 0)	133	0.06	122	0.12	1.752*
Bank Account (Yes = 1, No = 0)	120	1.83	121	1.83	0.200
Length of Residence at cur address (months)	133	163.26	122	195.35	1.673*
Employment Sector (1 = Government, 0 = Private Sector)	123	1.65	122	1.61	-0.577
Number of months worked at current employer	120	77.03	122	88.61	1.094
Work telephone (Yes = 1, No = 0)	123	0.89	122	0.96	2.143**
Home telephone (Yes = 1, No = 0)	133	0.32	122	0.34	0.216
Gross monthly income (Rand)	124	2053.06	122	1958.51	-0.593
Net monthly income (Rand)	124	1461.84	122	1570.99	1.054
Monthly debt-to-net income ratio	112	0.15	122	0.11	-1.781*
Average no. of loans with other lenders at time of application	122	1.75	114	1.54	-1.184
Total number of loans that were 2 – 3 months in arrears at time of application	122	0.25	114	0.07	-3.436***
Total number of loans that were 4 – 9 months in arrears at time of application	122	0.29	114	0.03	-4.973***
Total number of bad-debt write-offs at time of loan application	133	0.45	122	0.09	-4.471***

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels of significance, respectively.

Similar to the Pretoria branch, there was no statistically significant difference between accepted and rejected sample applicants in relation to having a bank account. Accepted Pietermaritzburg applicants, on average, lived longer at the current residential address than rejected applicants (195 months versus 163 months), this difference being statistically significant at the 10% level. The applicant's employment sector may indicate the potential stability of future income streams that are important for securing debt repayments.

Unlike applicants at the Ladysmith and Pretoria branches, most Pietermaritzburg applicants worked in the private sector (fewer applicants employed in the government sector were accepted). Although accepted Pietermaritzburg applicants, on average, had worked for longer at their current employer (89 months versus 77 months), this information was less important in the credit granting decision. Very few Pietermaritzburg applicants had telephones in their homes and so branch staff focused on contactability at work, unlike the Ladysmith and Pretoria staff. Most accepted applicants did, on average, have a work telephone, while rejected applicants did not (the difference was statistically significant). Unlike at the Ladysmith and Pretoria branches, there was no statistically significant difference in average monthly gross and net income between accepted and rejected applicants. Average monthly incomes of Pietermaritzburg applicants were lower than those of Ladysmith and Pretoria applicants. This reflected the relatively lower salaries and wages paid by the private sector jobs taken by these low-income individuals compared to those in the government sector. Similar to Pretoria and Ladysmith, the Pietermaritzburg branch staff focus on the debt-to-income ratio - accepted applicants had a statistically significantly lower mean ratio than rejected applicants. Payment profile and bad-debt write-off information was also just as important in credit screening for Pietermaritzburg branch staff as it was for Ladysmith and Pretoria staff. Applicants with more payment profiles in arrears and more bad-debt write-offs were likely to be rejected. A summary of the characteristics whose means were statistically significantly different between the rejected and accepted sample applicants in terms of the four pillars in credit assessment at the three MFO1 branches is given in Table 5.10.

Table 5.10 Summary of Statistically Significant Different Characteristics between Accepted and Rejected MFO1 Sample Applicants, 1998/ 1999

Branch	Ladysmith	Pretoria	Pietermaritzburg
STABILITY	Significance level		
Age	10%	ns	ns
Gender	ns	10%	10%
Married	ns	ns	ns
Single	5%	ns	ns
Home ownership type	ns	ns	ns
Use of a Home Loan	ns	ns	10%
Use of a Bank Account	15%	ns	ns
Length of residence at current address	ns	10%	10%
Employment sector	ns	ns	ns
Length of employment at current employer	ns	ns	ns
CONTACTABILITY	Significance level		
Home telephone	5%	10%	ns
Work telephone	ns	ns	5%
AFFORDABILITY	Significance level		
Net monthly income	1%	1%	ns
Gross monthly income	ns	ns	ns
Debt-to-net income ratio	1%	1%	10%
CREDIT HISTORY	Significance level		
Recent inquiries	5%	5%	ns
Prior inquiries	1%	1%	1%
Number of loans with other lenders	1%	1%	1%
Payment profile arrears of 3 months or less	1%	1%	1%

STABILITY

Only the length of residence at the current address tends to be statistically significantly different between accepted and rejected sample applicants consistently across most of the branches.

Gender is highlighted for the Pretoria and Pietermaritzburg branches, while age was a discriminator at the Ladysmith branch. Different branch managers tend to weight stability indicators differently, depending on the region where they operate.

CONTACTABILITY

Accepted sample applicants tend to have a home telephone contact number. It tends to be easier to contact borrowers at home than at work. Although most sample applicants indicated that they did have a work telephone, most could not be contacted directly. In a factory environment, access to public telephones is limited to specific times, while messages left with the employer may not be passed on to the employee.

AFFORDABILITY

The difference in net monthly (disposable) income between accepted and rejected applicants was statistically significant at the Ladysmith and Pretoria branches. Managers are very aware of the level of debt relative to income - the mean difference in this variable for accepted and rejected loan applicants was statistically significant at all branches. It is also a legal requirement set out by the MFRC that lenders must observe disposable income levels after accounting for all existing commitments, to try and ensure that applicants do not borrow above their repayment capacities.

PREVIOUS CREDIT HISTORY

This was the factor that had mean values that were most statistically significantly different between the accepted and rejected groups at all three branches (except for recent enquiries at the Pietermaritzburg branch). Sample applicants with a poor credit history were credit rationed, and most were rejected.

5.6.5 Descriptive Characteristics of Factors Affecting Loan Repayment at MFO1

5.6.5.1 Factors Affecting Loan Repayment at the Ladysmith Branch

Table 5.11 shows that 'good' borrowers, on average, are older than 'bad' borrowers at the Ladysmith branch (38 years versus 35 years), although the difference was not statistically significant. This is consistent with the observation that branch staff tended to accept loan applicants that are relatively older. There was no statistically significant difference in loan repayment performance between male and female Ladysmith borrowers, even though, on average, more male borrowers have problems repaying their debt than female borrowers. This suggests that Ladysmith branch staff incorrectly grant too many credit applications from males. Married borrowers had a marginally better loan repayment rate that borrowers that were not married, while single borrowers performed marginally worse than borrowers that were not single. However, loan repayment performance was not statistically significantly different between married and single borrowers, implying that marital status may not be a very useful predictor of potential loan default at this branch. Given that married applicants also had a relatively high acceptance rate at the Ladysmith branch, branch staff seem to make decisions that are consistent with risk-reducing behaviour and correctly identify low-risk loan applicants. Type of home ownership was not statistically significantly different between accepted and rejected applicants, nor did it significantly differentiate between 'good' and 'bad' Ladysmith

Table 5.11 Comparison of Means between 'Good' and 'Bad' Borrowers for the Ladysmith Branch of MFO1, 1998/ 1999

Characteristic	Good Borrowers		Bad Borrowers		t-value
	n	Mean	n	Mean	
Age (years)	53	38.04	20	34.51	1.346
Gender (Male = 1, Female = 0)	53	0.58	20	0.65	-0.501
Married (Married = 1, Other = 0)	53	0.53	20	0.45	0.590
Single (Single = 1, Other = 0)	53	0.36	20	0.50	-1.096
Own Home (Yes = 1, No = 0)	53	0.49	20	0.45	0.305
Live with employer (Yes = 1, No = 0)	53	0.02	20	0.05	-0.719
Live with parents (Yes = 1, No = 0)	53	0.21	20	0.30	-0.826
Rent (Yes = 1, No = 0)	53	0.08	20	0.15	-0.957
Location (Yes = 1, No = 0)	51	0.18	19	0.00	1.989**
Home Loan (Yes = 1, No = 0)	53	0.17	20	0.05	1.326
Bank Account (Yes = 1, No = 0)	53	1.91	20	1.80	1.220
Length of Residence at cur address (months)	53	176.77	20	159.10	0.452
Employment Sector (1 = Government, 0 = Private Sector)	53	1.40	20	1.75	-2.802***
Number of months worked at current employer	53	113.15	20	56.65	2.455***
Work telephone (Yes = 1, No = 0)	53	0.83	20	0.85	-0.201
Home telephone (Yes = 1, No = 0)	53	0.49	20	0.55	-0.447
Gross monthly income (Rand)	53	2 942.43	20	2 380.16	1.468
Net monthly income (Rand)	53	2 082.08	20	1 651.17	1.933**
Monthly debt-to-net income ratio	53	0.11	20	0.12	-0.088
Average no. of loans with other lenders at time of application	53	2.04	20	2.04	1.258
Total number of loans that were 2 – 3 months in arrears at time of application	53	0.11	20	0.20	-0.788
Total number of loans that were 4 – 9 months in arrears at time of application	53	0.02	20	0.00	0.612
Total number of bad-debt write-offs at time of loan application	53	0.04	20	0.15	-1.704*

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels of significance, respectively.

borrowers. Thus this information has relatively little influence in predicting potential loan repayment performance. Although borrowers living on locations performed better than those not living there, the statistical significance is misleading since there are relatively few counts for this variable. On average, more 'good' Ladysmith borrowers had a home loan and a bank account than did 'bad' borrowers. Those who have a home loan are probably more creditworthy and able to afford more debt due to their relatively higher income levels.

'Good' borrowers lived, on average, 178 months at their current address, while 'bad' borrowers had an average of 159 months (difference was not statistically significant). Since the average length of residence at the current address of accepted loan applicants was relatively higher, the results again indicate that Ladysmith branch staff decisions are consistent with risk-reducing behaviour in correctly identifying low-risk borrowers. Ladysmith borrowers working for the government sector tended to have a poorer loan repayment track record than borrowers employed in the private sector. Borrowers employed in the government sector tended to have higher levels of debt and were also less contactable (most were teachers teaching at rural schools). The results in Table 5.11 suggest that staff at the Ladysmith branch were ignoring potentially useful information about predictors of loan default, since more loan applicants employed in the government sector were granted credit.

'Good' borrowers had worked, on average, for longer at their employer at the time of application than 'bad' borrowers (113 months versus 57 months). This statistically significant difference implies that the credit granting decision based on this information is consistent with correctly identifying low-risk loan applicants, although the information may not influence assessing creditworthiness. Having a home or a work telephone did not significantly separate high- and low-risk borrowers. This may be due to the stringent credit rationing applied using this variable which plays a key role in MFO1's financial technology. 'Good' borrowers had a significantly higher mean net monthly income than did 'bad' borrowers. This characteristic thus seems to be used correctly to identify low-risk borrowers. Net income levels influenced the loan approval process, with applicants having relatively lower monthly net incomes being severely credit-rationed. The mean gross monthly income for 'good' borrowers was also relatively higher, but the difference was not statistically significant. Gross monthly income was not a key determinant in the credit granting decision where branch managers focused more on disposable income in estimating ability to repay future debt. There was no significant difference between the mean debt-to-income ratios for 'good' and 'bad' borrowers. This does not imply that this variable does not influence loan default, but rather that its effect has been reduced by the stringent credit rationing criteria applied by branch staff using this criterion.

There was no statistically significant difference between the mean number of previous loans with other lenders for 'good' and 'bad' borrowers, or between the numbers of payment profiles in arrears. The main reason for this is the extent to which loan applicants that have arrears on their payment profiles are credit rationed. Almost all loan applicants that had arrears on at least one of their payment profiles were rejected. It is, therefore, not possible to draw conclusions about the influence of this information in determining the probability of loan default. The difference in mean total number of bad-debt write-offs for 'good' and 'bad' borrowers was statistically significant. Most of the borrowers with previous bad-debt write-offs were delinquent, consistent with the branch managers accepting fewer applicants with bad-debt listings.

5.6.5.2 Factors Affecting the Loan Repayment at the Pretoria Branch

According to Table 5.12, 'good' borrowers at this branch were marginally older than 'bad' borrowers, but the difference was not statistically significant. Similar to the Ladysmith branch, this agrees with the observation that branch managers tend to accept relatively older loan applicants. Although more male borrowers, on average, experienced loan repayment problems, the difference in means was not statistically significant. Married borrowers performed slightly better than the borrowers that were not married. Given that married applicants also had a relatively higher acceptance rate, Pretoria branch staff seem to make decisions that are consistent with risk-reducing behaviour and correctly identify low-risk loan applicants. Pretoria borrowers that own their homes, or that rent, had better loan repayment performance. Only the difference in means for Pretoria borrowers living with their parents was statistically significant. Borrowers living with their parents may be less established in their employment and may also have to contribute toward household expenses leaving less disposable income to service debt.

Relatively more 'good' borrowers had a home loan, although the difference in means between the groups was not statistically different. 'Good' borrowers lived, on average, 173 months at their current address, while 'bad' borrowers lived an average of 175 months there (difference in means was not statistically significant). There is no apparent explanation why 'more stable' borrowers would be more prone to loan repayment problems. Similar to the Ladysmith branch, borrowers employed in the government sector, on average, experienced more loan repayment problems than borrowers in the private sector. Government employees had higher debt levels given their relatively higher incomes, leaving less income to fund basic needs and any additional new debt.

Table 5.12 Comparison of Means between 'Good' and 'Bad' Borrowers for the Pretoria Branch of MFO1, 1998/ 1999

Characteristic	Good Borrowers		Bad Borrowers		t-value
	n	Mean	N	Mean	
Age (years)	78	36.98	35	35.15	1.040
Gender (Male = 1, Female = 0)	78	0.62	35	0.69	-0.714
Married (Married = 1, Other = 0)	78	0.53	35	0.51	0.111
Single (Single = 1, Other = 0)	78	0.36	35	0.43	-0.700
Own Home (Yes = 1, No = 0)	78	0.54	35	0.46	0.795
Live with employer (Yes = 1, No = 0)	78	0.01	35	0.03	-0.583
Live with parents (Yes = 1, No = 0)	78	0.27	35	0.43	-1.687*
Rent (Yes = 1, No = 0)	78	0.17	35	0.09	1.138
Location (Yes = 1, No = 0)	78	0.01	35	0.00	0.668
Home Loan (Yes = 1, No = 0)	78	0.21	35	0.17	0.415
Bank Account (Yes = 1, No = 0)	76	2.00	35	2.00	-0.075
Length of Residence at cur address (months)	78	173.19	35	175.40	-1.106
Employment Sector (1 = Government, 0 = Private Sector)	78	1.49	35	1.60	1.239
Number of months worked at current employer	78	93.56	35	74.71	1.501
Work telephone (Yes = 1, No = 0)	78	1.00	35	0.97	0.440
Home telephone (Yes = 1, No = 0)	78	0.60	35	0.46	0.610
Gross monthly income (Rand)	78	3 157.13	35	2 878.04	0.198
Net monthly income (Rand)	78	2 063.09	35	2 007.52	0.400
Monthly debt-to-net income ratio	77	0.14	35	0.13	0.101
Average no. of loans with other lenders at time of application	74	2.31	33	2.18	0.400
Total number of loans that were 2 – 3 months in arrears at time of application	74	0.15	33	0.09	0.705
Total number of loans that were 4 – 9 months in arrears at time of application	74	0.01	33	0.03	-0.588
Total number of bad-debt write-offs at time of loan application	74	0.12	35	0.31	-2.040**

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels of significance, respectively.

The results suggest that Pretoria staff may ignore potentially useful information about predictors of loan default since, on average, more loan applicants employed in the government sector were granted credit. 'Good' borrowers had worked, on average, for longer at their employer at the time of application. Hence the credit granting decision based on this information is consistent with correctly identifying low-risk loan applicants, although, similar to Ladysmith, this information may not be considered important for assessing creditworthiness.

Having a home or a work telephone did not significantly separate high- and low-risk borrowers. 'Good' borrowers had, on average, a higher gross and net monthly income than delinquent borrowers (R3 157 and R2 063 versus R2 878 and R2 007, respectively). Given that net and gross monthly income are higher for accepted loan applicants, this information seems to be used correctly to identify low-risk borrowers. Net income was a key predictor of loan approval, with applicants having relatively lower monthly net incomes being severely credit-rationed. The difference between the mean debt-to-income ratios was not statistically significant, suggesting that this information cannot differentiate between high- and low-risk borrowers in the Pretoria branch sample. Again, since this information influences the loan granting decision, those applicants with high debt commitments are severely rationed, leaving those applicants with acceptable debt-to-income ratios in the borrower pool. This results in very similar mean debt-to-income ratios for 'good' and 'bad' borrowers.

Similar to the Ladysmith branch, there was no statistically significant difference in the mean number of payment profiles in arrears between 'good' and 'bad' borrowers at Pretoria. The main reason for this is the extent to which loan applicants that have arrears on their payment profile were credit-rationed. Almost all Pretoria applicants that had arrears on at least one of their payment profiles were rejected. It is, therefore, again not possible to draw any conclusions about the influence of this information in determining the probability of loan default. The difference in the mean total number of bad-debt write-offs for 'good' and 'bad' borrowers was statistically significant, indicating that loan granting decisions based on bad-debt write-offs are consistent with a strategy of minimizing loan default.

5.6.5.3 Factors Affecting the Loan Repayment at the Pietermaritzburg Branch

Table 5.13 shows that 'good' borrowers were marginally younger than 'bad' borrowers, but again this difference was not statistically significant. Similar to the Ladysmith and Pretoria branches, more male borrowers, on average, had loan repayment problems, but the difference in means was not statistically significant. Married borrowers performed slightly better, and borrowers that were single performed slightly worse, at the Pietermaritzburg branch. Given that married applicants also had a relatively higher acceptance rate, Pietermaritzburg branch staff seem to make decisions that are consistent with risk-reducing behaviour and correctly identify low-risk loan applicants, even though the information on marital status does not separate low- and high-risk borrowers.

On average, Pietermaritzburg borrowers that own or rent their homes, or that live with their parents, tended to be 'bad', while those that live on the premises of their employer or in a location tended to be 'good'. Only the difference in means between 'good' and 'bad' borrowers renting their accommodation is statistically significant. Borrowers renting their accommodation may have less stable expected incomes, while the risk of not contacting them is higher since they are more mobile.

Table 5.13 Comparison of Means between 'Good' and 'Bad' Borrowers for the Pietermaritzburg Branch of MFO1, 1998/ 1999

Characteristics	Good Borrowers		Bad Borrowers		t- value
	n	Mean	n	Mean	
Age (years)	103	35.91	19	36.78	-0.349
Gender (Male = 1, Female = 0)	103	0.58	19	0.63	-0.396
Married (Married = 1, Other = 0)	103	0.49	19	0.47	0.093
Single (Single = 1, Other = 0)	103	0.49	19	0.37	0.935
Own Home (Yes = 1, No = 0)	103	0.21	19	0.26	-0.475
Live with employer (Yes = 1, No = 0)	103	0.07	19	0.00	1.167
Live with parents (Yes = 1, No = 0)	103	0.24	19	0.26	-0.189
Rent (Yes = 1, No = 0)	103	0.16	19	0.32	-1.677*
Location (Yes = 1, No = 0)	103	0.32	19	0.16	1.427
Home Loan (Yes = 1, No = 0)	103	0.12	19	0.16	-0.501
Bank Account (Yes = 1, No = 0)	102	1.82	19	1.89	-0.763
Length of Residence at cur address (months)	103	199.02	19	175.47	0.570
Employment Sector (1 = Government, 0 = Private Sector)	103	1.59	19	1.74	-1.187
Number of months worked at current employer	103	85.71	19	104.32	-0.890
Work telephone (Yes = 1, No = 0)	103	0.95	19	1.00	-0.976
Home telephone (Yes = 1, No = 0)	103	0.35	19	0.26	0.728
Gross monthly income (Rand)	103	2 006.34	19	1 699.19	0.985
Net monthly income (Rand)	103	1 617.56	19	1 318.50	1.345
Monthly debt-to-net income ratio	103	0.09	19	0.17	-2.329**
Average no. of loans with other lenders at time of application	96	1.51	18	1.72	-0.655
Total number of loans that were 2 – 3 months in arrears at time of application	96	0.07	18	0.06	0.233
Total number of loans that were 4 – 9 months in arrears at time of application	96	0.02	18	0.06	-0.840
Total number of bad-debt write-offs at time of loan application	103	0.06	19	0.26	-2.159**

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% levels of significance, respectively.

'Good' borrowers lived, on average, 199 months at their current address, while 'bad' borrowers lived an average of 175 months at their current address, but the difference in means was not statistically significant. Given the difference in length of residence at the current address for accepted and rejected applicants, the results again indicate that the Pietermaritzburg branch manager's decisions are consistent with risk-reducing behaviour in correctly identifying low-risk sample borrowers. As at the Ladysmith and Pretoria branches, borrowers employed in the government sector, on average, experienced more loan repayment problems than borrowers employed in the private sector. These government employees tended to have higher debt levels given their relatively higher incomes, leaving less income to service basic needs and any additional new debt. Unlike both Pretoria and Ladysmith staff, Pietermaritzburg staff correctly identified government employees as being potentially more risky and hence credit-rationed them more, although this information is not statistically significant in differentiating between high- and low-risk borrowers. 'Good' Pietermaritzburg borrowers had worked, on average, for 77 months at their employer at the time of application compared to 89 months by 'bad' borrowers (difference in means was not statistically significant).

Having a home or a work telephone did not statistically significantly separate high- and low-risk borrowers. 'Good' borrowers had, on average, a higher gross and net monthly income than delinquent borrowers (R2 006 and R1 617 versus R1 699 and R1 319, respectively). The difference between the means is not statistically significant suggesting that, similar to Ladysmith and Pretoria, this information does not separate 'good' and 'bad' borrowers. The ratios of monthly debt commitments to net income suggest that 'good' borrowers, on average, have less debt relative to income than do 'bad' borrowers. The difference in mean monthly debt-to-income ratios was statistically significantly different for the Pietermaritzburg borrowers, indicating that debt commitments influence loan default and that the branch manager correctly uses this information to identify low-risk loan applicants.

Similar to the Ladysmith and Pretoria branch results, there was not a statistically significant difference in the mean number of payment profiles in arrears between 'good' and 'bad' borrowers. The main reason for this is the extent to which loan applicants that have arrears on their payment profile are credit-rationed. Most of the Pietermaritzburg applicants in arrears were rejected. It is, therefore, again not possible to draw any conclusions about the influence of this information in determining the probability of loan default. The mean difference in total number of bad-debt write-offs for 'good' and 'bad' borrowers was statistically significant, indicating that the loan granting decisions based on bad-debt write-offs are consistent with a strategy of trying to minimize loan default at the Pietermaritzburg branch.

Table 5.14 summarises this section by reviewing those characteristics for which the mean values were statistically significantly different between 'good' and 'bad' MFO1 borrowers. This gives some insight into which variables may be useful predictors of loan repayment performance as proxies for client stability, contactability, affordability and previous credit loan history.

STABILITY

Very few of the means of the stability indicators used by MFO1 were statistically significantly different between 'good' and 'bad' clients. Employment sector and length of employment at the current employer were only significantly different between these groups at the Ladysmith branch. These results may reflect a small sample problem, or sample applicants with poor performance at other lenders and who were rationed out have led to a lack of variability in the stability indicators across groups.

Table 5.14 Summary of the Significance Levels of Differences in the Means of the Characteristics used to Assess MFO1 Sample Borrower Loan Repayment Performance, 1998/ 1999

Branch	Ladysmith	Pretoria	Pietermaritzburg
STABILITY	Significance level		
Age	ns	ns	ns
Gender	ns	ns	ns
Married	ns	ns	ns
Single	ns	ns	ns
Home ownership type	ns	ns	ns
Use of a Home Loan	ns	ns	ns
Use of a Bank Account	ns	ns	ns
Length of residence at current address	ns	ns	ns
Employment sector	1%	ns	ns
Length of employment at current employer	1%	ns	ns
CONTACTABILITY	Significance level		
Home telephone	ns	ns	ns
Work telephone	ns	ns	ns
AFFORDABILITY	Significance level		
Net monthly income	5%	ns	ns
Gross monthly income	ns	ns	ns
Debt-to-net income ratio	ns	ns	ns
CREDIT HISTORY	Significance level		
Recent inquiries	ns	ns	ns
Prior inquiries	ns	ns	ns
Number of loans with other lenders	ns	ns	ns
Payment profile arrears of 3 months or less	ns	ns	ns
Payment profile arrears of 3 months or more	ns	ns	ns
Previous judgements	10%	ns	ns
Previous bad debt write-offs	10%	5%	1%

CONTACTABILITY

Mean telephone contact values at home or at work were not statistically significantly different between 'good' and 'bad' MFO1 borrowers.

AFFORDABILITY

The influence of affordability was difficult to assess since the rationing criteria applied to this factor by MFO1 branch managers was so stringent.

PREVIOUS CREDIT HISTORY

The differences in the means for previous credit history between 'good' and 'bad' borrowers were not statistically significant for the proxy showing bad debt listings at the credit bureau. Again, the credit rationing criteria based on clients' previous credit history were very strict, making it difficult measure the impact of this factor on loan repayment performance.

The empirical analyses that formally estimate models of credit rationing and loan default for MFO1 are compared in the next section. This will help to show whether variables that are predict credit-rationing well, can also predict subsequent loan repayment performance.

5.7 Econometric Methods to Estimate the Economic Models

5.7.1 Single Equation Models

The statistical modeling technique used to estimate the probability function (F) depends on the functional form of F. The common forms of the probability function include logit with

$$F(\beta x) = 1/(1 + e^{-x\beta}), \qquad (5.15)$$

probit with

$$F(\beta x) = \Phi(\beta x), \qquad (5.16)$$

where Φ is the cumulative normal distribution function, and the linear probability model with

$$F(\beta x) = \beta x \qquad (5.17)$$

Linear discriminant analysis has also been used to estimate equation (5.4) (Reichert *et al.*, 1983). The linear probability model and linear discriminant analysis will not be used in this study to estimate equation (5.4). The main problem with the linear probability model is that $F(\beta x|x)$ is not constrained to lie between 0 and 1 as a probability should. Amemiya (1981) suggests that this defect can be corrected by defining F = 1 if $F(\beta x|x) > 1$ and F = 0 if $F(\beta x|x) < 0$, but concludes that this produces unrealistic kinks at the truncation points of the cumulative distribution and recommends not using the linear probability model in the final stages of modeling probabilities. In addition, heteroskedasticity in the error term as a result of model specification make the Ordinary Least Squares (OLS) estimates of β inefficient in a linear probability model (Maddala, 1983).

Linear discriminant analysis has been used in several studies to determine the characteristics that are able to best classify borrowers as either 'good' or 'bad', or loan applicants as either accepted or rejected (Eisenbeis, 1978; Reichert *et al.*, 1983). Discriminant analysis, under assumptions of multivariate normality, closely resembles both the linear probability model and the logistic regression model, and so has often been used for comparative analysis purposes (Maddala, 1983; Amemiya, 1981). The most important assumption underlying discriminant analysis is that the variables describing members of the groups being evaluated are multivariate normally distributed. This assumption is clearly violated, in particular, by models employing categorical independent variables. However, the discriminant function is not necessarily less capable than the logit model in its ability to classify cases even where the assumption of multivariate normality is violated (Press and Wilson, 1978; Amemiya, 1981). Given the similarity between the linear probability and logit models, and the relative robustness of the discriminant function when its assumptions are violated, there may be a case for not discarding the discriminant function as a classification tool. An important differentiating characteristic between the discriminant function and the logit and probit models is the *direction of causality* between the dependent and independent variables.

The discriminant model specifies a joint distribution of y_i (dependent variable) and x_i (vector of independent variables), and not a conditional distribution of y_i given x_i. In a discriminant analysis the group status is pre-determined and a new observation is classified into one of the two groups based on measured characteristics. In qualitative response models such as the logit and probit, the determination of x_i *precedes* that of y_i and, therefore, group status is conditional on the determination of x_i. Thus the prediction of loan acceptance or loan default is not merely a problem of classification (Amemiya, 1981; Greene, 1992). As shown in section 5.3 and 5.4, the econometric models in this study are based on latent continuous dependent variables describing the credit rationing decision and the loan default outcomes.

The research issue is not one of merely classifying observations into pre-determined groups, but to rather predict the likelihood that a sample loan applicant will either be accepted or rejected, or repay or default on a loan, conditional on the characteristics of the loan applicant. Hence, given x_i, what will y_i be, and not given y_i, what is x_i, as in discriminant analysis. Therefore, the logit and probit are better suited to estimate the econometric models of credit rationing and loan default for this study. Logit and probit models are more robust where the assumptions of multivariate normality are not met, albeit only marginally (Press and Wilson, 1978). Logistic regression will be used to estimate the accept/reject and repay/default models at branch level. Equation (5.18) gives the logit model as specified by Maddalla (1983) and Greene (2000):

$$\begin{aligned} &\text{Prob}[Y_i = 1 | x_i] = \frac{e^{\beta x}}{1 + e^{\beta x}} \\ &\text{which can be re-written as} \\ &\log \frac{P_i}{1 - P_i} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + u_i \end{aligned} \tag{5.18}$$

The left hand side of equation (5.18) is the log odds ratio (or logit), which is a linear function of the β_j explanatory variables. This property of the logit model makes it intuitively easy to interpret and to use to estimate the single equation models. Note that $Y_i = 1$ in equation (5.18) represents the loan accept or default outcome, subject to information given about the x_i.

5.7.2 Estimating the Default Equation with Sample Selection Bias to Test the Efficacy of the Screening Process

The estimation of the economic model to test the efficacy of the loan screening mechanism at MFO1 accounts for the sample selection bias, but requires the estimation of two equations. Hunte (1993) used the tobit model to estimate parameters that affect the loan granting decision and subsequent loan repayment performance. Although the dependent variables in the specification used were continuous, the assumptions under which the tobit model was applied to account for sample censoring are questionable. Hunte (1993) also did not specifically account for the sample selection bias.

Both dependent variables in equations (5.9) and (5.10) are qualitative, which rules out the use of the tobit model. Van de Ven and van Praag (1981) first proposed a bivariate probit model to account for the sample selection bias in a two-equation model where both dependent variables are qualitative and binary in nature. This model was also applied by Boyes *et al.* (1989), Greene (1992) and Roszbach (1998) to analyse factors influencing loan repayment performance, where the loan default equation had to be conditioned for the unobserved repayment performance of rejected loan applicants. The specification of this model as derived in Greene (1992) is:

$$\begin{aligned} \mathrm{Ln}\,(x_i, v_i, \rho) = {} & \sum\nolimits_{C=0} \Omega_i \ln(1-\Phi(\beta' v_i)) + \sum\nolimits_{C=0,D=0} \Omega_i \ln \Phi_2(-(\alpha' x_i + \delta \overline{S_i}), \beta' v_i, -\rho)) \\ & + \sum\nolimits_{C=0,D=1} \Omega_i \ln \Phi_2(\alpha' x_i + \delta \overline{S_i}, \beta' v_i, \rho) \end{aligned} \tag{5.19}$$

5.8 Empirical Results of the Estimated Empirical Models

This section estimates the qualitative response models that identify factors that affect the probability of credit rationing and of loan default for MFO1 sample clients. Separate logistic regression models were estimated for the samples at each branch and on the combined data for all three branches. The section also estimates factors that influence loan repayment performance using the bivariate probit model in order to condition for the incidental sample selection. This model is then used to evaluate the efficacy of the credit granting decision for MFO1.

5.8.1 Correlation Matrix for Independent Variables

Previous research on credit rationing and loan default models has seldom focused on the correlations between the independent variables (Reichert *et al.*, 1983; Mortensen *et al.*, 1988; Boyes *et al.*, 1989; Turvey, 1991; Miller and LaDue, 1991; Greene, 1992; Roszbach, 1998; Schreiner, 1999). The primary focus of these studies was on the ability of the credit models to correctly classify observations, rather than to focus on the statistical significance of individual parameter estimates. In such situations, multicollinearity is of little consequence (Maddala, 1992). Although part of the objective of this study is to review the predictive power of the statistical models, the main objective is to identify parameter estimates that significantly influence the probability that a sample MFO1 applicant will be credit-rationed, or that a sample MFO1 borrower will default. It is thus important to consider the intercorrelations between potential variables for the models, as multicollinearity masks the true contribution of each collinear explanatory variable to the final model (Maddala, 1992; Greene, 2000). The bivariate correlation matrix is used initially in Table 5.15 to identify significant correlations between potential independent variables to be included in the models.

Although the bivariate correlations are not a "fail-safe" method of identifying multicollinearity, the statistical significance tests of the correlation coefficients do indicate a potential problem. What the correlations do not show is whether this inter-correlation will be major problem in the regression models (Maddala, 1992). The client stability indicators used by MFO1 staff such as gender, age, marital status, length or residence at current address and employer type, show significant correlation coefficients. For instance, gender was significantly positively correlated with being married and negatively correlated with being single. These links are expected as most sample applicants are married and are government employees, do not have a home telephone and have been less credit active. Age was also significantly correlated with many of the other explanatory variables.

Having a home loan was also significantly correlated with age, marital status, banking details, length of residence at current address, employer type and length of employment at current employer. These correlations agree with *a priori* expectations that sample applicants with a home loan tend to be older, married, government employees that have been employed for a relatively longer period of time. Although the client stability and general demographic indicators of sample applicants were highly correlated, initial comparisons of means suggest that most of these variables are not important in the loan decision process. While their inclusion in the empirical models may not be warranted, the exclusion of these variables could lead to potential bias in the parameter estimates (Greene, 2000).

Table 5.15 Correlation Matrix of MFO1 Sample Applicant Characteristics, 1998/ 1999

	Gender	Age	Married	Single	Home Loan	Bank Details	Length at residence	Employer	Length at employer	Home phone	Work phone	Net Salary	Retail debt/ net salary	Total previous Loans
Gender	1.000	-0.006	0.177***	-0.104***	0.002	0.017	-0.005	0.102***	0.070	-0.128***	0.031	0.154***	-0.120***	-0.106***
Age	-0.006	1.000	0.479***	-0.560***	0.135***	0.061	0.195***	-0.084**	0.617***	-0.015	-0.023	0.006	-0.110***	-0.140***
Married	0.177***	0.479***	1.000	-0.883***	0.131***	0.048	-0.022	-0.021	0.352***	0.002	-0.056	0.094**	-0.059	-0.125***
Single	-0.104***	-0.560**	-0.883***	1.000	-0.141***	-0.080**	0.048	0.012	-0.394***	-0.049	0.036	-0.080**	0.062	0.108***
Home Loan	0.002	0.135**	0.131***	-0.141***	1.000	0.084**	-0.144***	-0.171***	0.177***	0.095**	0.056	0.095**	0.034	0.093**
Bank Details	0.017	0.061	0.048	-0.080**	0.084**	1.000	0.034	-0.135***	0.055	0.134***	0.003	0.133***	0.046	0.138***
Length at res	0.005	0.195**	-0.022	0.048	-0.144***	0.034	1.000	0.001	0.133***	-0.009	0.010	-0.119***	0.012	-0.014
Employer	0.102***	-0.084*	-0.021	0.012	-0.171***	-0.135***	0.001	1.000	-0.146***	-0.103***	0.144***	-0.132***	-0.104***	-0.131***
Length at employer	0.070	0.617**	0.352***	-0.394***	0.177***	0.055	0.133***	-0.146***	1.000	0.014	0.014	-0.023	-0.048	-0.043
Home phone	-0.128***	-0.015	0.002	-0.049	0.095**	0.134***	-0.009	-0.103***	0.014	1.000	-0.044	0.272***	0.055	0.210***
Work phone	0.031	-0.023	-0.056	0.036	0.056	0.003	0.010	0.144***	0.014	-0.044	1.000	-0.079**	0.064	0.083**
Net Salary	0.154***	0.006	0.094**	-0.080**	0.095**	0.133***	-0.119***	-0.132***	-0.023	0.272***	-0.079**	1.000	-0.166***	0.128***
Retail debt/ net salary	-0.120***	-0.110**	-0.059	0.062	0.034	0.046	0.012	-0.104***	-0.048	0.055	0.064	-0.166***	1.000	0.374***
Total prev loans	-0.106***	-0.140**	-0.125***	0.108***	0.093**	0.138***	-0.014	-0.131	-0.043	0.210***	0.083**	0.128***	0.374***	1.000
Arrears 3 months	-0.079**	-0.048	-0.037	0.037	0.002	0.018	-0.017	-0.064	0.019	0.040	0.046	0.012	0.149***	0.328***
Arrears 4 months	-0.018	-0.036	0.012	-0.015	-0.028	-0.008	-0.019	0.047	0.016	0.018	0.066	-0.025	0.116***	0.221***
Bad debt	-0.033	-0.047	-0.031	0.035	0.014	-0.008	-0.057	-0.017	-0.032	0.080**	-0.013	-0.036	0.100**	0.083**

Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

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Table 5.15 Correlation Matrix of MFO1 Sample Applicant Characteristics, 1998/ 1999 (continued)

	Arrears 3 months	Arrears 4 months	Bad debt
Gender	-0.079**	-0.018	-0.033
Age	-0.048	-0.036	-0.047
Married	-0.037	0.012	-0.031
Single	0.037	-0.015	0.035
Home Loan	0.002	-0.028	0.014
Bank Details	0.018	-0.008	-0.008
Length of res	-0.017	-0.019	-0.057
Employer	-0.064	0.047	-0.017
Length at employer	0.019	0.016	-0.032
Home phone	0.040	0.018	0.080**
Work phone	0.046	0.066	-0.013
Net Salary	0.012	-0.025	-0.036
Retail debt/ net salary	0.149***	0.116***	0.100**
Total prev loans	0.328***	0.221***	0.083**
Arrears 3 months	1.000	0.008	-0.003
Arrears 4 months	0.008	1.000	0.220***
Bad debt	-0.003	0.220***	1.000

Note: ** and *** indicate statistical significant at the 5% and 1% levels, respectively.

As expected, the income proxy variables were significantly positively correlated with the number of previous loans with other lenders. Sample MFO1 applicants with higher incomes tended to be more credit active and probably qualified for more credit than did lower income applicants. Clients with a high debt-to-income ratio also had relatively more loans in arrears (significant correlations between this ratio and the payment profile arrears variables). The total number of previous loans with other lenders was significantly correlated with most of the other variables. It was significantly negatively correlated with age, gender, marital status, and employer type, suggesting that younger, female sample applicants are more credit active. Age was significantly positively correlated with bank details, single loan applicants, telephone contact, the income proxies and payment profile arrears. This suggests that applicants with relatively more previous loans with other lenders were single, had contact details (requirement to access credit at other lenders), had a bank account, earned relatively more income and, because of their credit activity, had relatively more payment profiles that have been in arrears at some point.

The validity of including the total number of loans as a predictor can be questioned since it represents many other factors in the credit dimension that are better explained by the variables that it is correlated with. Payment profile arrears were strongly correlated with net income and total previous loans. The more loans the sample applicant had with other lenders, the greater were the arrears (this is expected since greater credit activity increase the likelihood of going into arrears at some stage). Bad debt write-offs were also significantly correlated with payment profiles that show serious arrears. This is expected since the likelihood that a loan showing serious delinquency will be written off is very high. The payment profile information was not significantly correlated with the demographic and personal characteristics of the sample applicants. This suggests that demographic characteristics have very little influence on loan repayment performance, with the main factors being debt-to-income levels and, possibly, previous arrears and bad debt write-offs. The next section discusses the expected relationships between these characteristics and loan applicant credit rationing and loan repayment performance.

The branch variables were also highly correlated with the remaining variables in the models, indicating that branch managers' decisions are mostly based on information that has proxies for stability, contactability, affordability, and credit history. The difference between the branch managers is in the *emphasis* placed on the different proxies. It is thus very difficult to isolate the effects of branch manager experience in statistical models. By estimating the individual credit rationing and loan default models for each branch, the individual branch effects can be better noted than in a combined model.

5.8.2 Independent Variables Included in the Empirical Models

Marital status, gender, bank details, home loan, and total number of previous loans with other lenders were excluded from the analysis. Both marital status and gender were not key variables in the credit-vetting procedure and there was no statistically significant difference between the means of these variables for 'good' and 'bad' borrowers. Although past studies have found that women have better loan repayment track records than men, this study found no statistically significant difference between female and male borrowers.

Inconsistencies in recording marital status also reduced the potential impact of this variable. Banking details and having a home loan were also not key credit rationing decision variables for MFO1 branch managers. Further exploratory analysis suggests that these indicators also have no influence on loan repayment performance. The total number of loans with other lenders was excluded from the analysis because the individual effects of these variables could not be isolated. This is linked to the way in which the credit bureau returned the data. Credit activity is also proxied sufficiently by the payment profile information since this variable counted the number of loans with arrears.

Prior to estimating the statistical models, the effects of these variables were estimated by means tests and additional regressions of each independent variable on the dependent variable (Hosmer and Lemeshow, 1989). These exploratory analyses found that different groupings of economic sector were important. Although the overall government/ private sector employment variable did not contribute significantly to the credit rationing and loan repayment decisions, branch managers do focus on particular employment sectors that are vulnerable at the time of application, and then ration loan applicants employed in those sectors more severely. The individual branch analyses were also not intended to test the efficacy of the loan granting decision because of sample size constraints. The bivariate probit model is extremely sensitive to the counts of observations for each independent variable per dependent variable category (Greene, 1997). These analyses were intended to highlight key factors affecting the credit rationing decision and to identify factors that influence subsequent loan repayment performance.

The default probabilities may hence have a slight downward bias. The estimated credit rationing and loan default models for each branch are given in the following sections.

5.8.3 Logit Model Results for Branches

The following sections report estimated logit models for each of the branches and the bivariate probit model for the combined sample. To test the estimated classification accuracy of the models, the data are split into two subsets, one being used to estimate the parameters in the logit model and the second being a holdout subset used to evaluate predictive accuracy (Reichert *et al.*, 1983). Given the relatively small sample sizes involved, 20% of the sample observations were randomly selected to constitute the holdout sample.

5.8.3.1 Credit Rationing Model for the Ladysmith Branch

Borrower age (LSMAGED), home telephone (HOMPHD), debt-to-income ratio (LSMNETSR), payment profiles with minor arrears (TO236M), payment profiles with major arrears (TO496M) and total number of bad debt write-offs (TOBDWO) are used as proxies for stability, contactability, affordability and credit history respectively. The expected signs and specifications for these variables are shown in Table 5.16.

Table 5.16 Definitions and Expected Signs of Parameter Estimates of Variables Affecting the Ladysmith Branch Credit Rationing Decision, 1998/ 1999

Variable Name	Description	Expected sign for effects on credit rationing Prob(C = 1)
	Stability	
LSMAGED	= 1 if sample applicant age ≥ 34 years = 0 if sample applicant age < 34 years	+
	Contactability	
HOMPHD	= 1 if sample applicant had a home phone = 0 if sample applicant did not have a home phone	+
	Monthly retail debt / Monthly net income	
LSMNETSR	= 1 if debt-to-net income ratio ≥ 0.15 = 0 if debt-to-net income ratio < 0.15	-
	Credit History	
TO236M	Total number of payment profiles that were 2-3 months in arrears at loan application	-
TO496M	Total number of payment profiles that were 4 or more months in arrears at the time of loan application	-
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	-

The binomial logit parameters estimated for this model presented in Table 5.17 had a residual deviance of 109.3, following a chi-squared distribution with 115 degrees of freedom (df), and showed no significant lack of fit for the overall model. The likelihood ratio test of the null hypothesis that the parameter estimates of the model equal zero (55.075) follows a chi-squared distribution with 6 degrees of freedom and indicates that the variables in the model contribute significantly to predicting P_{Accept} (Hosmer and Lemeshow, 1989; Menard, 1995).

The Wald statistic can be used to determine the significance of the individual parameter estimates. A disadvantage of this statistic is that for large parameter estimates the standard error is inflated which may lead to false acceptance of the null hypothesis that $\beta = 0$ (Aldrich and Nelson, 1984; Menard, 1995). Since the coefficients in Table 5.17 are relatively small, the Wald statistic shows that the coefficients estimated for HOMPH, LSMNETSR, TO236M, LSMAGED, TO496M and TOBDWO are significant at the 15%, 10%, 5% and 1% levels of significance, respectively.

Table 5.17 Estimated Credit Rationing Model for the Ladysmith Branch, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{accept}/P_{reject})$	Wald Statistic	Marginal Effects
Constant	+0.6760	2.4513	
LSMAGED	+1.4038	7.1939***	0.2493
HOMPH	+0.8106	2.6683^15%	0.1866
LSMNETSR	-0.7644	2.4080*	-0.1819
TO236M	-1.1771	5.0697**	-0.2553
TO496M	-3.0363	6.6725***	-0.3570
TOBDWO	-1.7799	9.4615***	-0.1480

Residual deviance = 109.301 (115 df)
Likelihood ratio test = 55.075*** (6 df)
Nagelkerke R^2 = 0.491

Classification of Observations

Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	32	17	65.3%
Accept	11	62	84.9%
		Overall Classification	77.1%

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The variables, LSMAGED and LSMNETSR were re-specified as dichotomous dummy variables to try and better identify the critical points at which the MFO1 Ladysmith branch manager regards these variables as reaching levels that indicate credit risk. A condition index of 4.314 indicates very mild multicollinearity and hence no further remedial action was taken (Greene, 2000). The estimated model classifies 77% of the observations correctly - 84% of the accepted and 65% of rejected sample applicants.

The signs of the estimated coefficients agree with *a priori* expectations. Sample applicants that were older; contactable at home; had a debt-to-income ratio below 15%; had few payment profiles with minor and major arrears, and with fewer bad debt write-offs, had a higher likelihood of being accepted. Although sample borrower age was significantly correlated with most of the stability and contactability measures in the study, individual analysis and comparison of means showed that none of the other stability indicators affected the loan granting decision of the Ladysmith branch manager. Since most of the other stability variables are excluded from the analysis, LSMAGED suggests that older, more responsible borrowers were deemed less risky and were thus less credit-rationed. The influence of contactability is confirmed with sample applicants that were not contactable at home having a greater likelihood of being rationed.

Contacting borrowers by telephone is a key component of MFO1's monitoring technology since no physical collateral is taken to increase the incentive of the borrower to repay. Lack of telephonic contact makes this technology ineffective, and increases the likelihood of the loan not being repaid. Sample applicants having a higher debt-to-income ratio have a greater likelihood of being credit-rationed, as they have less available disposable income to service the additional debt. The Ladysmith branch manager thus seems to be very aware of debt levels of sample applicants and tries not to over-commit potential borrowers.

Key rationing criteria for the Ladysmith branch manager also seem to be the manner in which loan applicants have handled their debt obligations with other lenders as shown by the payment profile information (TO236M and TO493M) and total bad debt write-offs. Applicants with any arrears on their payment profiles and who had any bad debt write-offs in the 24 months prior to the loan application at MFI1 were likely to be rejected. For instance, an applicant with one payment profile showing major arrears has an 89% probability of being rejected. It is debatable whether the strict credit rationing based on previous credit history is warranted given the inconsistency of the payment profile information.

The marginal effects in Table 5.17 indicate the change in probability for a unit change in the independent variable. For continuous independent variables the marginal effects are evaluated using the group means. The greatest change in probability is observed for increases in LSMAGED, TO236M and TO496M. If a sample applicant is older than 34 years, the probability of being accepted increases by 24.9 percentage points. The probability of being accepted decreases, on average, by 25.5 and 35.7 percentage points, respectively for applicants with minor and major arrears. Increases in payment profile arrears have the greatest marginal impact on the likelihood of applications being rejected.

Employing the same sample used to derive the parameter estimates to test the model's overall classification accuracy may lead to biased and overly optimistic classification results (Reichert *et al.*, 1983). The logit model was, therefore, re-estimated using a 20% holdout sample to test for predictive accuracy. The results in Table 5.18 for the residual deviance again show no significant lack of fit. The null hypothesis that the slope parameters are zero can be rejected, given that the likelihood ratio test is statistically significant at the 1% level.

Table 5.18 Estimated Credit Rationing Model for the Ladysmith Branch – Excluding Holdout Subset, 1998/ 1999

Variable Name	**Parameter Estimate $\ln(P_{accept}/P_{reject})$**	**Wald Statistic**	**Marginal Effects**
Constant	+1.1362	4.9401	
LSMAGED	+1.3010	4.8458**	0.1013
HOMPH	+0.4279	0.6086	0.2963
LSMNETSR	-0.5400	0.9351	-0.1293
TO236M	-1.2625	4.5362**	-0.2653
TO496M	-3.1629	6.9222***	-0.3598
TOBDWO	-1.9129	9.0971***	-0.1822
Residual deviance = 87.011 (98 df) Likelihood ratio test = 50.435**** (6 df) Nagelkerke R^2 = 0.523			

Classification of Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	26	12	68.4%
Accept	7	60	89.5%
		Overall Classification	81.9%
Classification of Holdout Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	3	8	27.2%
Accept	0	6	100.0%
		Overall Classification	52.9%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The model has relatively good predictive power with an overall 81.9% correct classification of observations. The signs of the parameter estimates agree with *a priori* expectations, although the estimates for HOMPH and LSMNETSR are not statistically significant. The debt-to-income ratio, LSMNETSR, is relatively highly correlated with the payment profile arrears and this may mask the effect of this variable somewhat. The classification power of the estimated model was good for accepted applicants but poor for rejected applicants, leading to an overall 53% correct classification. Although a classification cut-off of 0.5 was used, this should not markedly influence the classification power, as the proportions of accepted and rejected sample applicants are almost equal. This poor classification power may be a sample specific result.

5.8.3.2 Credit Rationing Model for the Pretoria Branch

Based on the comparison of means in Table 5.8, home telephone (HOMPHD), economic sector (CONMOW), debt-to-income ratio (PTANETSR), payment profiles with minor arrears (TO236M), payment profiles with major arrears (TO496M and total number of bad debt write-offs are used as proxies for contactability, stability, affordability and credit history, respectively. Loan applicants employed in the construction and motor manufacturing industries were deemed to have more secure expected incomes by the MFO1 Pretoria branch manager, as Gauteng is the hub of industrial development in SA and has several large motor manufacturing plants located in the Pretoria area. The CONMOW variable is thus hypothesized to have a positive relationship with the probability of being accepted, and a negative relationship with the probability of loan default. Expected signs for the proxies, and the variable specifications are shown in Table 5.19.

The binomial logit model for the Pretoria branch with a residual deviance of 253.828 in Table 5.20 shows no significant lack of fit. The null hypothesis that the parameter estimates of the model are zero can be rejected given the highly significant likelihood ratio test of 126.04 and the relatively high R^2 (0.483). The Wald statistic follows a chi-squared distribution with 1 degree of freedom, and shows that the parameter estimates for HOMPHD, CONMOW, TO236M, TO496M and TOBDWO are statistically significant at the 1% level. The PTANETSR is statistically significant at the 15% level, which may be due to the relatively high correlation between the debt-to-income ratio and having major arrears on payment profiles. A condition index number of 4.012 indicates only mild collinearity between the independent variables and hence no further remedial action was taken.

Table 5.19 Definitions and Expected Signs of Parameter Estimates of Variables Affecting the Pretoria Branch Credit Rationing Decision, 1998/ 1999

Variable Name	Description	Expected sign for effect on credit rationing Prob(C = 1)
	Stability	
CONMOW	= 1 if sample applicant employed in the motor manufacture and construction industry = 0 otherwise	+
	Contactability	
HOMPHD	= 1 if sample applicant had a home phone = 0 if sample applicant did not have a home phone	+
	Monthly retail debt / Monthly net income	
PTANETSR	= 1 if debt-to-net income ratio ≥ 0.18 = 0 if debt-to-net income ratio < 0.18	-
	Credit History	
TO236M	Total number of payment profiles that were 2-3 months in arrears at loan application	-
TO496M	Total number of payment profiles that were 4 or more months in arrears at the time of loan application	-
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	-

The signs of the estimated coefficients agree with *a priori* expectations. Applicants that were more contactable at home, employed in the construction and motor manufacturing sectors, with lower debt-to-income ratios, had fewer payment profiles showing minor or major arrears and with fewer bad debt write-offs were more likely to be accepted at the Pretoria branch. Expected stability of future income is key.

Table 5.20 Estimated Credit Rationing Model for the Pretoria Branch, 1998/ 1999

Variable Name	Parameter Estimate $Ln(P_{accept}/P_{reject})$	Wald Statistic	Marginal Effects
Constant	0.2249	0.7158	
HOMPHD	1.0463	10.7024***	0.1778
CONMOW	2.4943	8.1745***	0.5510
PTANETSR	-0.4027	1.5488$^{15\%}$	-0.0066
TO236M	-1.4646	21.7136***	-0.0819
TO496M	-2.7342	13.5244***	-0.1243
TOBDWO	-1.1559	19.8008***	-0.0787

Residual deviance = 253.828 (282 df)
Likelihood ratio test = 126.046*** (6 df)
Nagelkerke R^2 = 0.483

Classification of Observations

Observed	Predicted: Reject	Predicted: Accept	Percent Correct
Reject	150	33	81.9%
Accept	24	80	77.4%
		Overall Classification	80.3%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The construction and motor manufacturing sectors are relatively well established in Gauteng, implying reasonably stable expected future incomes for borrowers. Ability and willingness to repay debt are also key decision criteria for the Pretoria branch manager. Sample applicants with monthly retail debt commitments below 18% of their monthly net income had less likelihood of being credit-rationed. This highlights the awareness amongst branch managers of the importance of not over-committing sample loan applicants to debt. Both the Pretoria and Ladysmith branch managers have credit-rationed sample applicants with debt commitments well below the 25% level recommended in the Report on the Impact of Credit and Indebtedness of Clients (2001).

Willingness to repay debt probably weighs most heavily in the credit decision of the Pretoria branch manager. Sample applicants with debt at other credit institutions that had any arrears were likely to be fully credit-rationed. Similarly, sample applicants with bad debt write-offs are less likely to be granted credit. This implies that the information provided by the credit bureau is of critical importance. The result also highlights the use of reputational capital as a collateral substitute. Sample applicants with less reputational capital (lower payment profile arrears and bad debt write-offs) were less likely to be granted credit by MFO1 staff. It also highlights the reliance that branch staff place on this information which can be detrimental to the credit granting process where staff are inexperienced at interpreting this information (as in the case of the newly appointed Pretoria branch manager). Credit may be rationed too strictly where this reduces credit sales and puts pressure on the branch to remain financially viable.

The logit model was re-estimated using a random sample of 80% of the observations to test the classification accuracy of the model and the stability of the parameter estimates. The residual deviance in Table 5.21 shows no significant lack of fit, while the statistically significant likelihood ratio test shows that the selected variables together contribute towards the explanatory power of the model. The signs of the parameter estimates are the same as those in the full model, and the coefficients are of a similar size. The estimated model performs relatively well - about 87% of rejected, and 77% of accepted applicants in the holdout subset were correctly classified.

The marginal effects of the estimated model indicate that the probability of being accepted rose by about 20 and 52 percentage points, respectively, for sample applicants having a home phone and employed in the construction and motor manufacturing industries. The marginal effects for TO236M, TO496M and TOBDWO are the average over the range of the continuous variable. The likelihood of being credit-rationed increases most for applicants that had one payment profile with mild arrears or major arrears. The probability of being accepted with one payment profile in minor arrears falls from 35% to 11%, while that showing major arrears decreases from 40% to 4%. Severe credit rationing occurs as result of a poor credit track record at other lenders.

Table 5.21 Estimated Credit Rationing Model for Pretoria – Excluding Holdout Subset, 1998/ 1999

Variable Name	Parameter Estimate $Ln(P_{accept}/P_{reject})$	Wald Statistic	Marginal Effects
Constant	0.113	0.142	
HOMPHD	1.072	8.846^{***}	0.1984
CONMOW	2.332	6.825^{***}	0.5204
PTANETSR	-0.214	0.347	-0.0387
TO236M	-1.432	15.713^{***}	-0.0875
TO496M	-2.659	12.317^{***}	-0.1328
TOBDWO	-1.036	14.117^{***}	-0.0821
Residual deviance = 200.831 (215 df) Likelihood ratio test = 93.659^{****} (6 df) Nagelkerke R^2 = 0.469			

Classification of Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	111	27	80.4%
Accept	19	65	77.4%
		Overall Classification	79.3%

Classification of Holdout Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	39	6	86.7%
Accept	5	17	77.3%
		Overall Classification	83.6%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.8.3.3 Credit Rationing Models for the Pietermaritzburg Branch

Time worked at the current employer (LENGEMP), economic sector (CONSTRUC), having a work telephone number (TELWORK), debt-to-income ratio (PMBNETSR), payment profiles with minor arrears (TO236M), payment profiles with major arrears (TO496M) and total number of bad debt write-offs are used as proxies for stability, contactability, affordability and credit history, respectively, given the results in Table 5.9. Pietermaritzburg applicants employed in the construction industry were deemed to be greater credit risks as little new development was taking place in and around the Pietermaritzburg area at the time of the study. Applicants employed in the construction industry (CONSTRUC) are more likely to be credit-rationed and to experience loan repayment difficulties (hypothesized sign of ECONPMB is positive). The expected signs for these proxies, and the variable specifications are shown in Table 5.22.

Table 5.22 Definitions and Expected Signs of Parameter Estimates of Variables Affecting the Pietermaritzburg Branch Credit Rationing Decision, 1998/ 1999

Variable Name	Description	Expected sign for effect on credit rationing Prob(C = 1)
	Stability	
LENGEMP	= 1 if > 48 months = 0 if ≤ 48 months	+
CONSTRUC	= 1 if sample applicant employed in construction industry = 0 otherwise	-
	Contactability	
TELWORK	= 1 if loan applicant had work telephone = 0 if loan applicant did not have work telephone	+
	Monthly retail debt / Monthly net income	
PMBNETSR	= 1 if debt-to-net income ≥ 0.25 = 0 if debt-to-net income < 0.25	-
	Credit History	
TO236M	Total number of payment profiles that were 2-3 months in arrears at loan application	-
TO496M	Total number of payment profiles that were 4 or more months in arrears at the time of loan application	-
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	-

The full sample model estimated in Table 5.23 shows no significant lack of fit, with a residual deviance of 239.286 and 213 degrees of freedom. The chosen variables as a group explain the variability in the model (highly significant likelihood ratio test). The length of employment at current employer and the debt-to-income ratio were re-specified as dichotomous variables to better identify the critical points at which the Pietermaritzburg branch manager regards these variables as indicators of high-risk clients, and to partly reduce the incidence of multicollinearity. A condition index of 9.607 indicates mild collinearity, so no corrective action was taken (Greene, 2000). The significant Wald statistics confirm the rejection of the null hypothesis that the individual parameter estimates equal zero.

Table 5.23 Estimated Credit Rationing Model for the Pietermaritzburg Branch, 1998/ 1999

Variable Name	**Parameter Estimate $Ln(P_{accept}/P_{reject})$**	**Wald Statistic**	**Marginal Effects**
Constant	-0.2207	0.1145	
LENGEMP	0.4959	$2.2978^{15\%}$	0.1225
CONSTRUC	-1.3048	$2.0930^{15\%}$	-0.2751
TELWORK	1.0639	2.8248^{*}	0.2375
PMBNETSR	-0.8502	4.3272^{**}	-0.1994
TO236M	-1.5376	10.9659^{***}	-0.2349
TO496M	-2.6043	15.4044^{***}	-0.2762
TOBDWO	-1.1006	11.4196^{***}	-0.2461

Residual deviance = 239.286 (213 df)
Likelihood ratio test = 66.864^{****} (7 df)
Nagelkerke R^2 = 0.348

Classification of Observations

Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	77	30	71.9%
Accept	22	92	80.7%
		Overall Classification	76.5%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The coefficients for LENGEMP, CONSTRUC, TELWORK, PMBNETSR, TO236M, TO496M, and TOBDWO are statistically significant at the 15%, 10%, 5% and 1% levels of significance, respectively. The model classifies 72% of the rejected and 81% of the accepted sample applicants correctly. An overall 77% of sample applicants are classified correctly. The signs of the parameter estimates agree with *a priori* expectations. Applicants that were employed for longer at their current employer, were not employed in the construction industry, were contactable by telephone at work, had a retail debt-to-income ratio over 25%, and had loans with other lenders that are not in arrears were less likely to be credit-rationed. Stability and contactability indicators tended to have less influence than affordability and creditworthiness in the credit rationing decision. Sample applicants that were employed for more than 48 months at the current employer were regarded as having relatively more stable expected future income streams. Applicants employed in the construction industry in the Pietermaritzburg area were regarded as relatively more risky due to the increased likelihood of retrenchment or erratic employment given the relatively lower levels of investment in fixed infrastructure in the city at the time of the study. Since sample applicants in this area are less contactable at homes, more emphasis is placed on contact at work. This may also be part of the reason why applicants working in the construction industry were credit-rationed more (their level of contactability at work is poorer).

Similar to managers at the Ladysmith and Pretoria branches, much emphasis is placed on how the applicant has managed credit at other lending institutions. Applicants that had loans in arrears with other lending institutions were less likely to be accepted. The marginal effects show that this is a key decision variable, with the average probability of being accepted falling by 23 and 27 percentage points, respectively, for applicants that had loans with minor or major arrears.

The logit model was re-estimated using an 80% randomly selected sample to test the classification power of the model, and robustness of the parameter estimates. The residual deviance in Table 5.24 shows no significant lack of fit, while the statistically significant likelihood ratio test indicates that the variables included contribute together in predicting the likelihood that a sample applicant will be accepted. The model classifies 67% of the rejected and 81% of the accepted applicants correctly (overall 75% correct classification rate).

Table 5.24 Estimated Credit Rationing Model for the Pietermaritzburg Branch - Excluding the Holdout Subset, 1998/ 1999

Variable Name	Parameter Estimate $Ln(P_{accept}/P_{reject})$	Wald Statistic	Marginal Effects
Constant	-0.325	0.214	
LENGEMP	0.492	$2.078^{15\%}$	0.1222
CONSTRUC	-0.865	0.850	-0.2013
TELWORK	1.028	$-1.028^{15\%}$	0.2359
PMBNETSR	-0.840	3.508^{**}	-0.2003
TO236M	-1.261	6.780^{***}	-0.2222
TO496M	-2.184	10.453^{***}	-0.2724
TOBDWO	-0.989	8.632^{***}	-0.2438
Residual deviance = 212.812 (180 df) Likelihood ratio test = 47.620^{****} (7 df) Nagelkerke R^2 = 0.298			

Classification of Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	79	30	67.0%
Accept	18	79	81.4%
		Overall Classification	74.5%

Classification of Holdout Observations			
Observed	Predicted		Percent Correct
	Reject	Accept	
Reject	16	0	100.0%
Accept	4	13	76.5%
		Overall Classification	87.9%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The parameter estimates carry the same sign as those estimated using the full sample, while the absolute size of the parameter estimates is not much different to those in the full model, except for CONSTRUC. The estimated model in Table 5.24 has relatively good classification power, with 100% of the rejected and 77% of the accepted sample applicants being classified correctly (marginally less than the model estimated using the full sample).

5.8.3.4 Summary of Credit Rationing Models

The lender must be able to correctly predict loan default in order to promote business viability. The probability of repayment is influenced by external factors such as the stability of future expected income streams, and by borrower behaviour, which, in turn is influenced to some extent by the incentives embedded in the loan contract to repay the loan (Navajas, 1999a). The financial technology used by the lender must, therefore, be able to separate high- and low-risk borrowers and to offer an appropriate contract that aligns the incentives of the borrower with those of the lender. The type of financial technology used by the lender will partly determine what type of client can be offered credit, and what are the important decision factors in predicting the potential risk of the loan applicant. Lender MFO1 uses a financial technology that focuses on granting credit to low-income individuals employed in the formal sector, who have no or very little tangible collateral to secure the loan. Factors that reduce the default risk within the limits of this financial technology are thus important determinants of the credit rationing decision.

The applicant's place of employment influences the stability of expected future income streams. Branch managers, therefore, look at the economic sector in which the sample applicant is employed. Sectors may differ from region to region but the sector is something that all branch managers consider in their rationing decision. Other stability indicators, like marital status, gender and home ownership type, did not have as much influence on this decision. Since MFO1 cannot take collateral, staff cannot physically visit every borrower to ensure loan repayment, and telephonic contact is critical. Again, the financial technology targets a specific type of clientele to mitigate the risk of loan default and ensure that the contract can be monitored effectively to align the incentives of the borrower to those of the lender. Consistent across all three branches, all branch managers require that applicants be contactable by telephone at home or at work.

Another key criterion in the credit decision across all three branches was the loan applicant's credit history, which shows his/her commitment to repaying debt. In essence the financial technology used by MFO1 substitutes reputational collateral for physical collateral. Sample applicants with less reputational capital were more severely credit-rationed because the technology depends on reputational capital to reduce the potential risk of default. However, the interpretation of information received from the credit bureau remains critical. Different arrears definitions and different credit policies lead to inconsistencies in the data reported by the bureau, and branch staff must understand this as it impacts on their decision to grant credit. Staff training in correctly using the bureau information is important if MFO1 wants to ensure more consistent decisions across branch staff. The next section reviews the factors that influence loan repayment performance at the three branches of MFO1.

5.8.4 Empirical Logit Model Results for Loan Repayment

The models estimating factors that influence loan default for the individual branches were exploratory - they are not scoring models, nor do they explicitly test the efficacy of the loan granting decision. Rather, these models identify factors that influence loan default once sample applicants have been screened and are considered creditworthy by MFO1 staff. The estimated default probabilities of the models may be downwardly biased as a result of not being conditioned for the incidental sample selection. However, individual sample sizes for the branches were relatively small with low proportions of observed defaults. This causes instability in the bivariate probit model and, therefore, the bivariate probit model will only be estimated for the full sample (Greene, 1997).

5.8.4.1 Loan Repayment Model for the Ladysmith Branch

Borrower age (LSMREAGE), economic sector (ECONLSM), relationship to closest relative or friend, and ratio of monthly debt commitments to net monthly income (INDENSAC) were included as proxies for stability, contactability and affordability. The variables' specifications and expected parameter signs are shown in Table 5.25.

Table 5.25 Definitions and Expected Signs of Parameter Estimates of Variables Influencing Loan Applicant Default at the Ladysmith Branch, 1998/ 1999

Variable Name	Description	Expected sign for effect on loan default Prob(D = 1)
	Stability	
LSMREAGE	= 1 if sample borrower age > 26 years = 0 if sample borrower age ≤ 26 years	-
ECONLSM	= 1 if sample borrower was employed in textiles, beverage and education sectors = 0 otherise	-
	Contactability	
RCRF12	= 1 if sample borrower's closest relative was friend or cousin, uncle, aunt = 0 if sample borrower's closest relative was parent, wife, sister or brother	-
	Monthly retail debt / Monthly net income	
INDENSAC	Ratio of monthly instalment of MFO1 loan/net salary	+

The loan default model in Table 5.26 has a residual deviance of 63.624 with 68 degrees of freedom, showing no significant lack of fit. The statistically significant likelihood ratio test indicates that the variables as a group contribute to influencing the probability of loan default. The Wald statistics are significant at the 10%, 5% and 1% levels, respectively, indicating that the individual parameter estimates are significantly different from zero. Loan default probability at the Ladysmith branch was influenced by borrower age (LSMREAGE) and economic activity (ECONLSM), the relationship of the borrower to the provider of a personal reference (RCRF12), and the debt-to-income ratio (INDENSAC). The signs of the estimated parameter estimates agree with *a priori* expectations. Sample borrowers under 26 years of age, employed in the textiles, beverage and education sectors, whose personal reference was provided by a friend, uncle, aunt or cousin, and who had a higher debt-to-income ratio were more likely to default.

Table 5.26 Estimated Loan Default Model for the Ladysmith Branch, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{accept})$	Wald Statistic	Marginal Effects
Constant	1.5434	1.7963	
LSMREAGE	-2.4536	8.6313***	-0.5282
ECONLSM	-1.3613	4.53411**	-0.2478
RCRF12	-1.3601	4.1954**	-0.2519
INDENSAC	5.7612	2.8425*	0.0499

Residual deviance = 63.624 (68 df)
Likelihood ratio test = 22.103**** (4 df)
Nagelkerke R^2 = 0.378

Classification of Observations (Cut Point = 0.5)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	49	4	92.4%
Bad	11	9	45.0%
		Overall Classification	79.4%

Classification of Observations (Cut Point = 0.3)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	43	10	81.1%
Bad	5	15	75.0%
		Overall Classification	79.5%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Although the Ladysmith branch manager already credit-rationed younger sample applicants, it is evident that rationing borrowers who are 34 years of age may be too strict and should perhaps be adjusted to the 26-year cut-off point. This outcome is again conditional on the loan applicant being accepted. Younger borrowers may have less stable incomes, be relatively inexperienced in managing credit, and may take the contractual obligation to repay the loan less seriously (since they have less experience of the consequences of defaulting on credit). They also have lower incomes and hence may have less capacity to meet their debt obligations. The textiles industry in SA has faced increased competition in recent years due to the lowering of import tariffs, and a number of textile factories have closed. This negatively affects the expected stability of future income streams and increases the risk that sample borrowers employed in this sector will default. Borrowers employed in the education sector usually taught at rural schools that were relatively distant from the branch, reducing their contactability. Although many of these teachers gave the telephone number of the regional education department, very few could be contacted directly at the school where they worked. The reduced ability to monitor the sample applicants may have reduced their incentives to repay, and hence increased the likelihood of loan default.

Providers of client references on the application form affect the borrower's contactability. If a sample borrower is not contactable, or does not respond to telephonic follow-up calls, the credit control staff at MFO1 phone the reference provider. The study results indicate that where this provider has no direct relationship with the sample borrower, the effectiveness of the reference increases. Parents, brothers and sisters may have less incentive to relay messages to the borrower, or may co-operate less with the credit control staff, than would friends or more distant relatives. This finding should be interpreted with caution, as it may be very sample specific.

The debt-to-income ratio used in the loan default analysis for the Ladysmith branch differs somewhat from to the debt-income ratio used in the credit-rationing model. Given that sample applicants with relatively high retail debt-to-net income ratios were severely rationed, few sample borrowers at the Ladysmith branch had high retail debt-to-net income ratios, reducing the variability of this ratio and, hence, its potential role in explaining default. The ratio of the monthly instalment of the MFO1 loan granted to net income seemed to play a more influential role. Sample borrowers that used a larger proportion of their monthly net income to repay the

MFO1 loan were more likely to default. There are a number of competing needs for disposable income, especially for low-income borrowers who may allocate proportionately more of their income to paying for daily living expenses.

Where more of the income is taken up by debt, loan repayments are likely to suffer, since the available income is first allocated to other, more important needs. While the branch manager may be cautious in granting credit to already highly indebted loan applicants, it is important that loans should not exceed the applicants' repayment capacity. The marginal effects show that age, economic sector where employed, and provision of a reference had the greatest impact on the probability of default. The estimated model classifies 92% of the accepted and 45% of the rejected sample applicants correctly (overall 79% correct classification rate). There are a relatively large number of Type II classification errors where defaulting borrowers are incorrectly classified as current. The cut-point of 0.5 in the classification rule is normally used, but there are potential problems, particularly if the sample sizes differ markedly, and the pay-offs between falsely classifying a defaulting borrower as a current borrower, and a current borrower as a defaulting borrower, are not the same (Greene, 2000). If there are a low proportion of defaulters in the sample, then the prediction rule, based on a cut-point of 0.5 may have difficulty in predicting a defaulter (Greene, 2000). This is evident in Table 5.27 for the classification table on a cut-off point of 0.5. Discussions with management at MFO1 identified that it is more costly to incorrectly classify a potential defaulting borrower as a good borrower, than it is to incorrectly classify a potentially current borrower as a defaulting borrower. There is, therefore, some merit in adjusting the cut-off point to reflect the sample proportions of defaulters, in order to better classify defaulters. The disadvantage is that by adjusting the cut-off point to better classify defaulters, the number of Type I errors will increase (Greene, 2000).

Table 5.27 Estimated Loan Default Model for the Ladysmith Branch - Excluding the Holdout Subset, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{good})$	Wald Statistic	Marginal Effects
Constant	2.3862	3.3734	
LSMREAGE	-2.9883	9.3517^{***}	-0.6308
ECONLSM	-1.6214	5.1978^{**}	-0.3257
RCRF12	-1.7514	5.5856^{**}	-0.3137
INDENSAC	5.7624	2.4712^{*}	0.8629
Residual deviance = 53.728 (62 df) Likelihood ratio test = 26.177^{***} (7 df) Nagelkerke R^2 = 0.464			

Classification of Observations (Cut-off point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	44	4	91.6%
Bad	10	9	47.3%
		Overall Classification	79.1%
Classification of Observations (Cut-off point = 0.3)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	41	7	85.4%
Bad	4	15	78.9%
		Overall Classification	88.8%
Classification of Holdout Observations (Cut-off point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	3	2	60.0%
Bad	1	0	0.0%
		Overall Classification	50.0%
Classification of Holdout Observations (Cut-off point = 0.3)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	3	2	60.0%
Bad	1	0	0.0%
		Overall Classification	50.0%

Note: *, ** and *** indicate significance at the10%, 5% and 1% levels, respectively.

Given that 25% of the sample borrowers defaulted at Ladysmith, the cut-off point was lowered to 0.3. The model then predicted 75% of defaulting and 81% of current borrowers correctly. The resulting increase in Type I errors is thus relatively small. The model in Table 5.27 re-estimated the loan default situation with an 80% random sample of borrowers, and shows no significant lack of fit, with the parameter estimates being statistically significant. The signs of the estimated parameter estimates agree with those of the full model. The absolute values of the parameter estimates were also relatively close to those of the full model. Given the small size of the 20% holdout sample (only 6 observations), it is difficult to draw conclusions about the classification ability of the model. The model classifies 60% of the current borrowers and none of the defaulters correctly.

5.8.4.2 Loan Repayment Model for the Pretoria Branch

Time spent at current employer (NEWLENGR), home ownership type (NEWHOME), economic sector (PTAECON), telephone contact at home (TELPTR) and total bad debt write-offs (TOBDWO) were used as proxies of stability, contactability and credit history given the analysis of means in Table 5.12. The variables are specified with the expected parameter signs in Table 5.28. The statistically significant likelihood ratio test in Table 5.29 indicates that the variables included in the model influence the probability of loan default. The parameter estimates are statistically significant at the 10% and 5% levels of significance, and their signs agree with *a priori* expectations.

Table 5.28 Definitions and Expected Signs of Parameter Estimates of Variables Influencing Loan Applicant Default at the Pretoria Branch, 1998/ 1999

Variable Name	Description	Expected sign for effect on loan default Prob(D = 1)
	Stability	
NEWLENGR	= 1 if length of employment at current employer > 120 months = 0 if ≤ 120 months	-
NEWHOME	= 1 if sample borrower owns home = 0 otherwise	-
PTAECON	= 1 if sample borrower employed in construction, motor manufacturing, entertainment, and non-core financial services sector = 0 otherwise	-
	Contactability	
TELPTR	= 1 if sample borrower had home phone and contact phone = 0 otherwise	+
	Credit History	
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	+

Sample applicants that rented or owned a home, lived for more than 120 months at their current residential address, not employed in the construction, motor manufacturing, security, financial services, education and entertainment sectors, were contactable at home and had no bad debt write-offs had less probability of defaulting. Applicants that owned their homes may have relatively more stable incomes compared to sample applicants who live with their parents, on their employer's property or in a location. Applicants who have lived for longer at their current residential address may also be more stable with better contactability. The PTAECON variable suggests that applicants employed in the construction, motor manufacturing entertainment, education, security and financial services sector were more likely to default.

These results contrast with the initial credit-rationing criteria used by the Pretoria branch manager where applications from the construction and motor manufacturing sectors were less risky. There may, therefore, be a degree of error in incorrectly accepting high-risk sample applicants. Sample borrowers working in the entertainment (mostly gambling industry) and security sectors may be relatively more risky since they work shifts and are more difficult to contact. In addition, job security, and hence income stability tended to be lower in these sectors. Borrowers who worked in the financial services industry were mostly cleaning and clerical staff that were being retrenched due to the outsourcing some of these functions.

Table 5.29 Estimated Loan Default Model for the Pretoria Branch, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{good})$	Wald Statistic	Marginal Effects
Constant	-0.2533	0.2908	
NEWHOME	-0.8290	2.8199*	-0.1716
NEWLENGR	-1.1292	3.2516*	-0.1941
PTAECON	1.2155	6.5676***	0.2530
TELPTR	-0.9832	4.2607**	-0.1935
TOBDWO	0.9234	3.4616*	0.4617
Residual deviance = 116.494 (107 df) Likelihood ratio test = 23.375**** (5 df) Nagelkerke R^2 = 0.263			

Classification of Observations (Cut-off Point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	70	8	89.7%
Bad	21	14	40.0%
		Overall Classification	74.3%

Classification of Observations (Cut-off Point = 0.3)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	62	16	79.5%
Bad	14	21	60.0%
		Overall Classification	73.5%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

It is difficult to explain why sample borrowers employed in the motor manufacturing and construction sector were perceived as relatively more risky. These borrowers either work on a construction site or in a factory environment where contactability can be a particular problem. Few of the employers allow the borrowers to take calls while on shift, and according to credit controllers, few employers in these sectors pass on a telephonic message to their employees. This reduces the effectiveness of the monitoring technology and thus may increase the potential for moral hazard. The probability of loan default for a sample applicant employed in these sectors increased by about 25 percentage points. Sample borrowers that were contactable were less likely to default. Those that still had bad debt write-offs had a higher probability of defaulting. This supports the already strict credit-rationing criteria based on previous loan defaults used by the branch managers, and shows that once borrowers have defaulted on a loan, the likelihood that it will happen again is very high. The marginal effect of this variable is the highest - the probability of loan default for a sample borrower with one previous bad debt write-off increases by 46 percentage points.

The estimated model in Table 5.29 correctly classifies nearly 90% of current, and 40% of the defaulting borrowers (overall correct classification of 74%). Given that only 30% of the sample borrowers defaulted, the classification based on a cut-off point of 0.5 is likely to perform relatively poorly. With unequal costs of committing a Type I and a Type II error, reducing the cut-off point to 0.3 better classifies the defaulters at the cost of incorrectly classifying non-defaulters.

The estimated holdout subset model in Table 5.30 shows no significant lack of fit using 80% of the cases, with the signs of the parameter estimates being the same as those in the full model. The estimated classifies 88% of the current borrowers and 0% of the defaulters correctly (overall 47% correct classification). Reducing the cut-off point to better reflect the population proportions and reduce the costly Type II error improves the overall classification to 64%, and classifies 56% of the defaulters correctly.

Table 5.30 Estimated Loan Default Model for the Pretoria Branch - Excluding Holdout Subset, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{good})$	Wald Statistic	Marginal Effects
Constant	-0.509	1.047	
NEWHOME	-0.995	3.213*	-0.1883
NEWLENGR	-0.774	1.313	-0.1241
PTAECON	1.244	5.469*	0.2373
TELPTR	-0.847	2.612*	-0.1513
TOBDWO	1.080	4.103**	0.3400

Residual deviance = 93.062 (90 df)
Likelihood ratio test = 19.082*** (5 df)
Nagelkerke R^2 = 0.262

Classification of Observations (Cut-off point = 0.5)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	66	4	94.3%
Bad	19	7	26.9%
		Overall Classification	76.0%

Classification of Observations (Cut-off point = 0.3)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	54	16	77.1%
Bad	10	16	61.5%
		Overall Classification	72.9%

Classification of Holdout Observations (Cut-off point = 0.5)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	8	1	88.8%
Bad	8	0	0.0%
		Overall Classification	47.1%

Classification of Holdout Observations (Cut-off point = 0.3)

Observed	Predicted Good	Predicted Bad	Percent Correct
Good	6	2	75.0%
Bad	4	5	55.6%
		Overall Classification	64.7%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.8.4.3 Loan Repayment Model for the Pietermaritzburg Branch

Economic sector (ECONPMB), borrower debt-to-income ratio (PMBINC), total number of recent inquiries (TOTRECINC), length of longest spell of arrears (LENGSPEL) and total bad debt write-offs (TOBDWO) were included as proxies for stability, affordability and credit history respectively, given the analysis of means in Table 5.13. The variables are specified with their expected parameter signs Table 5.31.

Table 5.31 Definitions and Expected Signs of Parameter Estimates of Variables Influencing Loan Applicant Default at the Pietermaritzburg Branch, 1998/ 1999

Variable Name	Description	Expected sign for effect on loan default Prob(D = 1)
	Stability	
ECONPMB	= 1 if sample borrower was involved in construction, motor manufacturing, and textile manufacturing = 0 otherwise	+
	Monthly retail debt / Monthly net income	
PMBINC	= 1 if debt/net income ratio $\geq$ 0.18 = 0 if debt/net income ratio < 0.18	+
	Credit History	
TOTRECINQ	Total number of recent inquiries at credit bureau	+
LENGSPEL	Length of longest spell of arrears on any payment profile	+
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	+

As only 15% of the accepted Pietermaritzburg sample applicants defaulted, this model was relatively unstable. The residual deviance of 74.176 in Table 5.32 shows no significant lack of fit, while the significant likelihood ratio test indicates that the variables as a group help to explain some variability in the model. The signs of the parameter estimates agree with *a priori* expectations. Sample applicants employed in the construction, motor manufacturing, textile manufacturing and cleaning sectors, that had over 18% of their net monthly income committed to repaying retail debt, that had more recent inquiries, and that had more bad debt write-offs were more likely to default.

Table 5.32 Estimated Loan Default Model for the Pietermaritzburg Branch, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{good})$	Wald Statistic	Marginal Effects
Constant	-3.9988	25.3406	
ECONPMB	1.8109	7.4863***	0.1810
PMBINC	1.4144	5.0441**	0.1626
TOTRECINQ	1.1130	2.7023*	0.1602
LENGSPEL	1.2632	1.8025	0.1033
TOBDWO	0.9983	3.3507*	0.1878
Residual deviance = 74.176 (107 df) Likelihood ratio test = 21.529*** (5 df) Nagelkerke R^2 = 0.263			

Classification of Observations (Cut-off Point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	90	6	93.7%
Bad	13	4	23.5%
		Overall Classification	83.1%

Classification of Observations (Cut-off Point = 0.15)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	71	25	74.0%
Bad	3	14	82.4%
		Overall Classification	75.2%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The positive sign for the ECONPMB coefficient agrees with the credit-rationing criteria employed by the Pietermaritzburg branch manager, and again suggests that workers in the construction and motor manufacturing sectors are relatively greater credit risks. Sample borrowers employed in the textile and cleaning sectors are also greater credit risks. The textile industry was experiencing increasing competition from cheaper imports at the time of the study.

Similar to the Ladysmith branch, employees in the textile industry were at greater risk of being retrenched or put on to short time.

The cleaning sector referred to employers that were supplying office cleaning and sanitary services to businesses in the Pietermaritzburg area. Sample borrowers in this sector were possibly at greater risk of losing their employment, and being more difficult to contact. This increased the risk of loan default due to less income stability and increased potential for moral hazard. Borrowers with a higher retail debt-to-income ratio had more likelihood of defaulting, with the probability of default increasing by 16 percentage points if the debt-to-income ratio exceeds 18%. The sign of the coefficient for PMBINC is contrary to that in the credit rationing equation, although the threshold of the ratio is lower. The result suggests that the Pietermaritzburg branch manager is justified in rationing sample applicants with higher debt-to-income ratios, as they are more likely to default.

Having less disposable income available makes these low-income borrowers more susceptible to negative income shocks. The total number of recent inquiries shows the recent credit activity of sample applicants. A higher number of recent inquiries means that there were more recent credit applications, and also possibly the likelihood that many of these applications were declined (potentially risky borrowers). This increased risk is confirmed by a greater likelihood of sample borrowers with more recent inquiries defaulting on their loans with MFO1. Accepted sample borrowers with more bad debt write-offs were more likely to default, which is consistent with the credit-rationing criteria applied by the branch manager. Economic sector and total number of bad debt write-offs caused the highest estimated marginal increase in the probability of default.

The likelihood of loan default by a sample borrower who worked in the motor manufacturing, textile and construction sectors increased by 18 percentage points. A similar increase was observed for sample applicants that have bad debt write-offs. Given the small proportion of defaulters in the sample, the 0.5 cut-off point for classification led to a relatively poor classification of defaulters. The estimated model correctly predicts 93% of current borrowers, and only 23% of the defaulters. The poor classification of defaulters is of concern, as the costs of incorrectly classifying a defaulter as current were considered quite high by MFO1 management.

Reducing the cut-off point to more closely represent that sample proportion for the Pietermaritzburg branch improves the model's ability to classify defaulters from 23% to 84%. Re-estimating the model in Table 5.33 using 80% of the sample observations confirms that the model is relatively unstable due to the relatively small proportion of defaulters. Although there is no significant lack of fit, and the parameter signs are consistent, the absolute size of these estimates, and of the significance levels, have changed (less robust model). The ability of this model to correctly predict the 20% holdout sample is not very good. It classifies current borrowers very well, but is unable to classify borrowers that default.

Table 5.33 Estimated Loan Default Model for the Pietermaritzburg Branch - Excluding Holdout Subset, 1998/ 1999

Variable Name	Parameter Estimate $\ln(P_{bad}/P_{good})$	Wald Statistic	Marginal Effects
Constant	-4.147	18.357	
ECONPMB	1.420	3.205^{*}	0.1522
PMBINC	1.905	5.741^{**}	0.2201
TOTRECINQ	0.769	0.821	0.1564
LENGSPEL	1.088	0.832	0.0844
TOBDWO	2.940	4.396^{**}	0.4379
Residual deviance = 49.266 (94 df) Likelihood ratio test = 25.065^{****} (5 df) Nagelkerke R^2 = 0.432			

Classification of Observations (Cut-off point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	75	2	97.4%
Bad	10	3	23.1%
		Overall Classification	86.7%
Classification of Observations (Cut-off point = 0.15)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	61	16	79.2%
Bad	3	10	76.9%
		Overall Classification	78.9%
Classification of Holdout Observations (Cut-off point = 0.5)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	18	1	94.7%
Bad	4	0	0.0%
		Overall Classification	78.2%
Classification of Holdout Observations (Cut-off point = 0.15)			
	Predicted		Percent Correct
Observed	Good	Bad	
Good	13	6	68.4%
Bad	4	0	0.0%
		Overall Classification	56.5%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5.8.4.4 Summary of the Empirical Models

Several factors that influenced the credit rationing decision of the three branch managers were not predictors of loan default, most notably the payment profile arrears. This is mainly due to the strict credit rationing applied by branch managers to sample applicants who had payment profile arrears. Employment stability as proxied by the economic sector where employed and length of employment at current employer, entered the default equations, followed by available disposable income (debt-to-income ratio), and reputational capital (reflected by total bad debt write-offs).

Boyes *et al.* (1989) Greene, (1992) and Schreiner (1999) found similar results in their models of consumer loan default models. Kohl (2000) supports these results in his credit assessment guidelines by identifying two key factors influencing default probability for low-income borrowers as stability of income and affordability. Stability of income is determined by economic conditions and may vary as these conditions change. This implies that MFO1 staff must monitor local economic conditions to identify timeously which sectors are likely to be affected by economic changes. Employment sector also indirectly influences borrower contactability, since factory and construction workers were less likely to be contactable in their work environment. If home contact cannot be readily established, which is highly likely for shift workers, there is an increased likelihood of moral hazard, since MFO1 staff cannot optimally enforce the loan contract.

Low-income borrowers are already under financial pressure to meet their day-to-day living expenses, and so may resort to financing their liquidity shortfalls with debt (Report on Impact of

Credit and Indebtedness of Clients, 2001). Increased borrowings increase the likelihood that borrowers may experience loan repayment problems during an income shock. Borrowers with debt-to-income ratios over 18% are particularly vulnerable. Reputational capital was also a key determinant of loan repayment. Sample borrowers with bad debt write-offs had a greater likelihood of defaulting on the debt commitments with MFO1 across all branches. Reputational capital can be effective if applied consistently across the credit industry. The next section estimates the bivariate probit model in order to test the efficacy of the screening decisions taken by MFO1 branch managers and to estimate parameters for the loan default model that condition for the sample selection bias.

5.8.5 Efficacy of the Credit Screening Process and Estimation of Loan Default Equation to Account for Incidental Sample Selection

Proxies for stability, contactability, affordability and credit history, and the expected signs of their estimated coefficients are shown in Table 5.34. Proxies for stability include the loan applicant's length of residence at the current address (G90MON), time spent at the current employer (LENGEMP), and economic sector (ECONENT, ECONSTR). Having a home telephone (HOMPHD) was a proxy for contactability, while the debt-to-income ratio (DITRATNE) measured loan affordability. The loan applicant's previous credit history was proxied by total number of payment profiles with minor arrears (TO236M) and total number of previous bad debt write-offs (TOBDWO). More client stability indicators were included in the bivariate probit model to try and make it as encompassing of the initial credit granting decision as possible. Length of residence at current address, and length of employment at current employer were included, while two categorical variables identifying different employment sectors were added to the model. There was, however, considerable multicollinearity between length of employment at current employer and length of residence at current address, and for the economic indicator variables.

Table 5.34 Variable Definitions and Expected Sign of Parameter Estimates of Branch Credit Rationing Decision, 1998/ 1999

Variable Name	Description	Expected sign for effect on credit rationing Prob(C = 1)	Expected sign for effect on loan default Prob(D = 1)
	Stability		
G90MON	= 1 if length of residence at current address > 90 months = 0 if length of residence at current address ≤ 90 months	+	-
LENGEMP	= 1 if > 48 months = 0 if ≤ 48 months	+	-
ECONENT	= 1 if the loan applicant is employed in the entertainment, security, and non-core financial services sector, = 0 otherwise	+/-	+/-
ECONSTR	= 1 if the loan applicant is employed in the construction or motor manufacturing sector = 0 otherwise	+/-	+/-
	Contactability		
HOMPH	= 1 if sample applicant had a home phone = 0 if sample applicant did not have a home phone	+	-
	Monthly retail debt / Monthly net income		
DITRATNE	= 1 if debt/ net income ratio ≥ 0.18 = 0 if debt/ net income ratio < 0.18	-	+
	Credit History		
TO236M	Total number of payment profiles that were 2-3 months in arrears at loan application	-	+
TOBDWO	Total number of bad debt write-offs at the time of loan applicant	-	+

Maddala (1992) and Greene (2000) suggest that the collinearity between variables can be reduced by using fewer orthogonal principal components that are constructed from the original variables. The problem with this process is that if it is difficult to attach a clear interpretation to the principal components, the interpretation of the parameter estimates in the estimates equation becomes ambiguous. Since only two variables make up each of the two principal components, this may be less of a problem. The first principal component includes the two economic sector groups ECONENT and ECONSTR as shown in Table 5.35. Only the first principal component can be retained (Maddala, 1992), and it accounts for 55% of the variability in ECONENT and ECONSTR. The principal component for the economic sector is named ECON. High values of ECON show that sample applicants are employed in ECONSTR, while negative values will indicate that applicants are employed in the ECONENT sector.

Table 5.35 Principal Component Analysis of Applicant Economic Sector, 1998/ 1999

Principal Component	Eigen Value	% of Variance Explained
1	1.120	55.98%
2	0.880	44.02%

Where
ECONENT = 1 if the loan applicant is employed in the entertainment, security, and non-core financial services sector
= 0 otherwise.
ECONSTR = 1 if the loan applicant is employed in the construction or motor manufacturing sector
= 0 otherwise.

Principal Component Factors	Principal Component 1	Principal Component 2
ECONENT	-0.748	0.663
ECONSTR	0.748	0.663

For the length of employment and length of residence analysis in Table 5.36, the first principal component accounts for 56% of the variability in G90MON and LENGEMP. Both eigenvector coefficients are positive, suggesting that the first principal component measures the overall stability of sample applicants as determined by length of residence at current address and length of employment at current employer. This principal component is designated as STABIL in the bivariate probit analysis.

Table 5.36 Results of the Principal Component Analysis on Length of Residence and Length of Employment, 1998/ 1999

Principal Component	Eigen Value	% of Variance Explained
1	1.135	56.75%
2	0.865	43.25%
Where G90MON = 1 if sample applicant has lived for longer than 90 months at current address = 0 otherwise LENGEMP = 1 if sample applicant is employed for longer than 48 months at employer = 0 otherwise		
Principal Component Factors	Principal Component 1	Principal Component 2
G90MON	0.753	0.658
LENGEMP	0.753	-0.658

Two other variables had to be modified for the bivariate probit model due to the sensitivity of the model to low number of observations for a given variable per dependent variable category. Few observations for an independent variable result in convergence problems (Greene, 1997). First, TO496M which measures the number of payment profiles with serious arrears that a sample applicant had at the time of application, had to dropped from the model as too few accepted sample applicants had such profiles (including this variable prevented the bivariate probit model from converging). To account for the role of payment profile arrears, a variable accounting for the total number of payment profiles with mild arrears that the sample applicant had in the 18 months prior to the application (TOT23), was substituted. This variable increased the number of counts per dependent variable category in order to improve the ability of the model to converge. Similarly, the variable accounting for total bad debt write-offs was re-specified to account for the total number of bad debt write-offs that sample applicants had in the 18 months prior to applying for a loan at MFO1. The estimated bivarate-probit model reported in Table 5.37 has a residual deviance of 480.20 that shows no significant lack of fit. The parameter estimates are statistically significant at the 15%, 10%, 5% and 1% levels, respectively.

Table 5.37 Bivariate Probit Model of Loan Default, 1998/ 1999

	Parameter Estimate $Z(P_{accept}/P_{reject})$	t-value	Parameter Estimate $Z(P_{bad}/P_{good})$	t-value
Constant	0.4009	4.575	-0.0892	-0.133.
HOMPHD	0.3938	3.252***	-0.3204	-1.406[15%]
ECON	0.0774	1.460[15%]	0.0776	0.7308
STABIL	0.1387	2.432**	-0.1789	-2.504**
DITRATNE	-0.2995	-2.401**	0.4053	2.271**
TOBDWO	-0.9249	-11.252***	0.9568	4.925***
TOT236M	-0.6828	-6.529***	0.3472	0.6223
			ρ = -0.9006	-1.306
Residual Deviance = 480.20 (618 df)				

Classification of Accept/Reject Observations (Cut-off point = 0.5)			
	Predicted		
Observed	Reject	Accept	Percent Correct
Reject	192	147	56.6%
Accept	45	248	84.6%
		Overall Classification	69.6%
Classification of Good/Bad Observations (Cut-off point = 0.5)			
	Predicted		
Observed	Good	Bad	Percent Correct
Good	150	72	67.6%
Bad	28	43	60.6%
		Overall Classification	65.9%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The signs of the parameter estimates for the model predicting the likelihood of a sample applicant being accepted agree with *a priori* expectations. Those applicants who had a home phone, more stable expected incomes, fewer payment profiles with arrears and fewer bad debt write-offs were more likely to be accepted. The model classifies 56.6% of the rejected and 84.6% of accepted sample applicants correctly (overall classification rate of 69%).

The signs of the parameter estimates in the loan default equation suggest that those borrowers who were contactable; more stable in that they have lived for longer at their current address and have worked for longer at their current employer, had lower debt-to-income ratios and bad debt write-offs in the last 18 months, were less likely to default. The default equation classifies 67% of the current and 60% of delinquent sample applicants correctly (overall correct classification rate of 65.9%). Boyes *et al.* (1989) and Greene (1992) also found that sample applicant income and previous credit history, as supplied by the credit bureau, were key determinants in the credit rationing decision. Sample applicants with higher incomes and a 'cleaner' credit history were more likely to be accepted. Boyes *et al.* (1989) also identified sample applicants who were stable (lived longer at their current address) as having a significant influence on the credit rationing decision. These findings support the results in this study, where sample applicants with lower debt burdens and fewer arrears records at the credit bureau were more likely to be accepted.

The positive and statistically significant parameter estimate for HOMPHD in the rationing equation, and the negative and significant parameter estimate for HOMPHD in the loan default equation, indicate that the branch managers at MFO1 have used this information correctly to identify low-risk sample applicants (quadrant I in Table 5.2). Applicant contactability thus seems to be a key predictor of the extent of credit rationing and the likelihood of loan repayment performance. Similarly, the negative and significant parameter estimate for DITRATNE in the rationing equation, and the positive and significant parameter estimate for DITRATNE in the loan default equation, indicate that branch managers have correctly used the debt-to-income ratio information to identify potential high-risk loan applicants (quadrant IV of Table 5.2).

The positive coefficient estimate of ECON in the credit rationing equation together with the positive coefficient estimate in the default equation suggests that branch managers have incorrectly accepted high-risk loan applicants. Those applicants employed in the motor manufacturing and construction sector tended to be greater credit risks than anticipated by branch managers. The non-significant parameter for ECON in the default equation suggests that information on the economic sector in which the sample applicants work may not be useful in the loan granting decision as it has little bearing on loan default. Boyes *et al.* (1989) also found that economic sector was a relatively weak predictor of loan default.

Since the economic sectors in which sample applicants were employed were relatively disaggregated, this finding may be very sample specific. The stability of employment as proxied by economic sector can clearly affect ability to repay a loan. A larger sample size would have perhaps highlighted this better. The positive and statistically significant parameter estimate for STABIL in the credit rationing equation, and negative and statistically significant parameter estimate for STABIL in the loan default equation, suggest that branch managers have correctly used applicant stability to identify potential low-risk borrowers. Those applicants who lived longer at their current address and who have worked for longer at their current employer were more likely to be accepted and less likely to default. More stable applicants may be easier to monitor and may also have relatively more stable future incomes for servicing debt.

The negative and statistically significant parameter estimate for TOBDWO in the credit rationing equation, and the positive and statistically significant parameter estimate in the loan default equation, suggest that branch managers have correctly used this information to identify potentially high-risk borrowers. Those applicants with previous bad debt write-offs were more likely to be credit-rationed and were also more likely to default. Boyes *et al.* (1989) and Greene

(1992) report similar results. The negative coefficient estimate for TOT23 in the credit rationing equation, and the positive coefficient in the loan default equation, imply that branch managers have correctly used payment profile information to identify potential high-risk borrowers, although the parameter estimate is not statistically significant in the loan default equation. Again, it would be incorrect to conclude that such information is not a predictor of loan default.

Applicants with arrears were severely credit-rationed, leaving relatively few applicants with arrears being accepted. This could have created too little variability in the data to show anything meaningful in the loan default equation. If a larger sample of applicants in arrears had been accepted, it may have been possible to quantify the effect of arrears on predicting loan default. The correlation between the error terms of the two equations (ρ) is negative, implying that the unexplained tendencies to grant credit are negatively correlated with those of loan default. Branch managers at MFO1 tend to be conservative and would rather over-ration applicants than grant loans to potentially more risky, but also more profitable, applicants. This is also evident in the signs of the parameter estimates. The information at the loan application stage is more likely used to correctly ration high-risk sample applicants than to accept low-risk applicants.

This result differs from those of Boyes *et al.* (1989) and Greene (1992) who found that unexplained tendencies to grant credit were positively correlated with predicting the probability of loan default. Boyes *et al.* (1989) linked this to a lending policy that attempts to seek out sample applicants that may be more risky, but also more profitable. Branch managers at MFO1 tended to be conservative and try to minimize potential loan default. A possible explanation for this is that MFO1 may already have acceptance rates at which satisfactory profit is being made. Any further increase in acceptance rates would increase the likelihood of earning lower profits.

One problem in using loan default models to predict default probabilities of "through the door" loan applicants is that these probabilities are downward biased because the model has not been specifically conditioned for selectivity bias. This bias results because default data are only observed for *accepted* sample applicants where these have already been screened and deemed creditworthy by the lender (Greene, 1992; Greene, 2000). The extent of such downward bias in predicted probabilities is shown in Table 5.38. Parameter estimates for both the conditional and unconditional probit models have similar signs, but the levels of statistical significance differ.

The effect of HOMPHD is much stronger in the conditional model, while that of ECON is much weaker. The effects of stability, debt exposure and total bad debt write-offs are much stronger in the conditional model than in the unconditional model, pointing to higher estimated probabilities of default. The parameter estimate for TOT36M also has the expected positive sign. The downward bias in the parameter estimates of the unconditional model is thus evident and can lead to the underestimation of default probabilities, particularly in scoring models that apply to the "though the door" loan applicants.

The average default probability for the sample applicant population is relatively lower at 28% for the unconditional model than the 57% for the conditional model. The conditional model would predict an average default probability of 29% for defaulters while the unconditional model would estimate 53%. Rejected sample applicants would have an average unconditional default probability of 32% and a conditional default probability of 64%. This level of downward bias was also reported by Greene (2000). Where MFOs try to develop credit scoring models, it is critical to account for the sample selectivity bias if the models are to correctly predict for the entire "though the door" loan applicant population. If this sample selectivity is not accounted for, the MFO's may commit serious Type I errors (incorrectly accept high-risk borrowers).

Table 5.38 Conditional and Unconditional Loan Default Models, 1998/ 1999

Variables	Unconditional Probit Model $Z(P_{bad}/P_{good})$		Conditional Probit Model $Z(P_{bad}/P_{good})$	
	Parameter estimate	t-value	Parameter estimate	t-value
Constant	-0.78955	-6.410	-0.0892	-0.133.
HOMPHD	-0.11922	-0.698	-0.3204	-1.406$^{15\%}$
ECON	0.21009	2.549***	0.0776	0.7308
STABIL	-0.14105	-1.734*	-0.1789	-2.504**
DITRATNE	0.35244	1.922*	0.4053	2.271**
TOT236M	-0.14100	-0.688	0.3472	0.6223
TOBDWO	0.87815	2.632***	0.9568	4.925***
	Average Default Probabilities			
Total Applicant Population	28%		57%	
Rejected Loan Applicants	32%		64%	
Accepted Loan Applicants	24%		48%	
Current Borrowers	22%		46%	
Defaulting Borrowers	29%		53%	

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Other methods of so-called "reject inference" have been used to account for sample selectivity bias. The most common method is to estimate the default model using the accept data only and then to compute the default probabilities for the reject data using the estimated model. Once this has been done, the loan default model is re-developed using the entire dataset (Hand, 2001). The problem with this approach is evident from Table 5.38 in that default probabilities for the rejected population are being estimated with downwardly biased parameters. The subject of reject inference is an area of intense debate in the credit industry but this issue is not explored further in this study.

The classification rates for the conditional and unconditional probit models are given in Table 5.39 and Table 5.40 for a range of cut-off points (comparing the classification of probabilities shows how different the conditional and unconditional models are). Given that the unconditional probit model has much lower average probabilities, it classifies a lower proportion of the defaulters correctly, while the conditional model almost seems to overcompensate.

Table 5.39 Differences in Classification Errors for Default Probabilities of the Conditional Bivariate Probit Model, 1998/ 1999

Cut-off Points	0.25	0.30	0.35	0.40	0.45	0.50	0.55
Percentage Correct 'Goods'	0.5%	6.3%	9.5%	41.5%	51.8%	67.6%	77.0%
Percentage Correct 'Bads'	98.6%	93.0%	90.1%	77.5%	69.0%	60.6%	45.0%
Percentage Type I error	1.4%	9.9%	9.9%	22.5%	31.0%	39.4%	55.0%
Percentage Type II error	99.5%	90.5%	90.5%	59.0%	48.2%	32.4%	22.1%

Table 5.40 Differences in Classification Errors for Default Probabilities of the Unconditional Bivariate Probit Model, 1998/ 1999

Cut-off Points	0.25	0.30	0.35	0.40	0.45	0.50	0.55
Percentage Correct 'Goods'	71.2%	86.0%	90.5%	95.9%	98.2%	98.6%	99.5%
Percentage Correct 'Bads'	53.5%	32.4%	25.4%	21.1%	18.3%	8.5%	5.6%
Percentage Type I error	46.5%	67.6%	74.6%	78.9%	81.7%	91.5%	94.9%
Percentage Type II error	28.8%	14.0%	9.5%	4.1%	1.8%	1.4%	0.5%

The proportion of the more costly Type I error is much lower for the conditional model than for the unconditional model. The issue that remains is what is the correct cut-off point to use for the conditional model, since the intuitive cut-off point of 0.25 that represents the population proportions has an unacceptably high level of type II errors. It seems as if the conditional model has been conditioned on the proportions of accepts and rejects in the sample which is closer to 50%. The estimated bivariate probit model shows that branch managers at MFO1 correctly use the information obtained from the loan applicant to screen for potential loan default risk. Again, key factors in the screening process are loan applicant income and previous credit history. The negative correlation coefficient suggests that the branch managers are somewhat conservative in their decision making process. This must always be weighed against expected profit, and it is important that MFO1 reviews the credit granting process, to ensure that the appropriate risk-return acceptance rate is maintained. A key aspect highlighted by the model is the inherent sample selection bias when estimating loan default models that ignore the information of rejected loan applicants. The next chapter also analyses factors that influence loan default, but identifies these factors in the context of medium-term agribusiness loans granted by study lender MFO2.

CHAPTER SIX

EMPIRICAL RESULTS OF LOAN DEFAULT MODELS FOR MFO2

This chapter reports the results of the estimated loan default model using data obtained from MFO2 over the period 1993 to 1994. Lender MFO2 is a finance institution providing short, medium and long-term agricultural loans to small-scale and emerging farmers. The model developed in this section is not conditional on the loan being accepted and hence should rather be treated a loan review model. As the theoretical background of the loan default analyses has been covered in Chapter five, the first section reviews the economic model for MFO2, followed by the data sampling methodology and descriptive statistics. The results of the econometric model are reported in section 6.6.

6.1 Objectives of the Analysis

The objective of this analysis is to estimate a loan default model that identifies characteristics, not only of borrowers that default, but also of borrowers that repay their loans with arrears. This additional category of loan repayment can markedly affect a MFO's liquidity, since the MFO depends on loan repayment to fund future loans. The information available from MFO2 was limited as no data was available on rejected loan applicants. The analysis, therefore, is restricted to identifying factors that affect loan repayment performance of medium-term agricultural loans made by MFO2. It is accepted that the result of this analysis will be downwardly biased.

No previous study in SA has estimated factors that affect loan repayment performance of clients using medium-term agricultural loans to finance equipment purchase at a development finance institution. This research may assist MFO2 and other MFOs who wish to provide this type of credit to account for key factors that may affect the repayment of such loans. Although the results may not be directly incorporated into a scoring model, they may highlight areas of additional focus for loan officers evaluating loan applications for this type of finance. The following section specifies the economic loan default model for MFO2.

6.2 Economic Model Specification for MFO2

Lender MFO2 provides short-, medium- and long-term agricultural loans to emerging commercial and small-scale farmers in KwaZulu-Natal, SA. The application process, particularly for the medium- and long-term loans, is relatively long. A loan application is initiated by an interview with the loan officer, to establish whether the loan applicant would qualify for a loan. An application form is then completed, followed by a visit to the business premises of the loan applicant. After all necessary documentation is completed, including financial statements, the loan application is reviewed by a committee that normally consists of the manager for agricultural credit at the branch, and the loan officer. Credit assessment criteria are determined by MFO2's credit policy, but also rely on the subjective evaluation of the loan officer. For the purposes of this study, repayment performance of medium-term agricultural loans will be assessed, as data on these loans was most readily available. The duration of medium-term agricultural loans was between 3 and 10 years. The model assumptions are as follows:

1) The loan applicant pool is heterogeneous with different risk levels, expected returns from their investment and probabilities of default.

2) Given borrower heterogeneity, MFO2 staff must screen loan applicants into different risk classes. Loan applicant screening is based on the information provided by the loan applicant and the policies and procedures as determined by MFO2's financial technology. Unlike MFO1, loan officers at MFO2 do not have any empirically derived diagnostic tools (credit scoring models) that can be used in the credit assessment.
3) MFO2 is a parastatal organization and hence its existence is not dependent on generating profits. Although enough income may be generated to cover operational costs, MFO2 is largely reliant on government funds to continue operating. Consequently, the interest rates that MFO charges are not market-related, but are lowered in line with its development objectives. The screening effect of interest rates may be reduced but the selection effect is still present (Hoff and Stiglitz, 1990; Herath, 1996). Although low interest rates will attract low-risk loan applicants, they will also lure a large number of high-risk borrowers to apply for credit. It is thus critical to have an effective screening technology to distinguish between high and low-risk borrowers.
4) Although the assets financed by MFO2 are pledged as collateral, the realizable value of this collateral is very low (due to poorly defined property rights and low market values of assets such as machinery and equipment) and, therefore, provides very little incentive for borrowers to repay the loan and thus has a negligible effect on the expected return of MFO2.
5) Information on rejected loan applications for MFO2 was difficult to come by, and so is, not included in the model. As the empirical default model does not condition for the absence of loan repayment performance of rejected loan applicants, the model cannot be used to predict potential default probabilities of all "through the door" loan applications.

At most, the results can be used to infer loan repayment performance of borrowers who have been deemed credit worthy (Miller and LaDue, 1991).

6) As the model can only be used to evaluate the loan repayment performance of borrowers with loans, the MFO2's expected return function can only be influenced by any potential risk-reducing measures that are adopted during the term of the loan. Such measures include increasing the levels of monitoring where borrowers are deemed to have become more risky during the term of the loan contract.
7) The model is assumed to be a single period model where the period spans over the entire duration of the loan (Eisenbeis, 1981).

The empirical default model is the same as that for MFO1 derived in equation (5.7) and (5.8) and is thus not repeated here. The vector of attributes x_i (as captured by MFO2 during the loan application process) is based on loan, business and personal variables as shown in Table 6.1.

Table 6.1 Definitions and Expected Signs for Variables used to Predict the Likelihood of Loan Default for MFO2

Vector of Explanatory Variables	**Expected sign for effect on loan default (D = 1)**
Loan characteristics	
Loan principal amount	-
Borrower's direct own equity contribution	-
Business characteristics	
Economic activity of the borrower (1 = if borrower funded a chicken or conract ploughing and cartage business venture, and 0 if borrower funded a maize milling or timer/sugarcane contracting harvesting and transport business)	+
Present annual income relative to annual debt obligations	-
Personal characteristics	
Previous loan history with MFO1 (1= Yes, 0 = No)	-
Gender of borrower (1 = Male, 0 = Female)	+

A proxy variable for asset collateral relative to loan size was not included in the analysis because the MFO2 file information on asset values was not reliable (staff constraints meant that asset value data were often not validated by visits to clients). Information on the monitoring activities of MFO2, number of years the borrower had been in the business, borrower education and family size were often missing from borrower case files, the possible impact of these variables on loan performance could not be evaluated.

Lenders can reduce the risk of client default by spending more resources on loan evaluation and supervision, which increases loan administration costs. Wealthier rural loan applicants with larger asset bases can reduce lender information collection costs by being able to readily pledge (verifiable) collateral. This could result in the concentration of loan portfolios amongst wealthy clients with larger loan sizes (Gonzalez-Vega, 1984). Lender behaviour could also be influenced by the applicant's resource allocation, risk management and product choices (Barry *et al.*, 1995). Consequently, more funds are likely to be available for investments having a better risk-return combination.

Sample borrowers with larger loans had larger asset bases, were diversified, had investments with higher net returns and dealt in well-established markets for their products. Wealthier borrowers may be better able to withstand negative income shocks by drawing on own assets and diverting less loan funds to personal consumption (Barham *et al.*, 1996). Loan size (LSIZE) as a proxy for larger, wealthier, surplus producing clients, is thus hypothesised to be negatively related to loan default.

A borrower's direct own equity contribution relative to total loan size (OWNLN) shows that the borrower has a stake in the proposed investment and reflects a risk-sharing agreement in which some of the risk of project outcome is borne by the borrower as an incentive to repay. This will not provide a first-best outcome, since as long as only part of the risk is borne by the borrower, he/she will equate his/her marginal cost of effort with his/her share and not with the total marginal product of the investment (Hayami and Otsuka, 1993: 21 - 55; Stiglitz and Weiss, 1981). In addition, a higher own equity contribution may reduce loan approval time since the lender may have less stringent information requirements. The variable OWNLN should, therefore, be negatively related to loan default.

Data on the sector financed was included to account for the relative riskiness of different business ventures. Contract harvesting and the carting of timber and sugarcane had well-established markets in KZN, with borrowers being able to deliver to the major processors of these products. In addition, maize milling is a service in demand in the rural areas where maize is predominantly grown for consumption purposes. The more regular cash flows implied by these factors would improve the potential repayment ability of these borrowers. Loans for the purchase of tractors and implements, although offering attractive potential returns, were deemed more risky by MFO2 lending staff because borrowers often failed to maintain the equipment used for contracting services.

Experience also shows that contractors involved in land preparation such as ploughing had liquidity problems as they seldom had enough work throughout the year (Ross, 1996). Chicken production enterprises, which involve relatively low capital outlay, faced intense competition, while increased feed costs and Newcastle disease had led to large losses and the consequent poor performance of such enterprises at the time of the study. The CONTRACT variable should, therefore, be positively related with loan default.

Gross annual income relative to annual debt obligations, LIQUID, indicates the borrower's ability to meet debt commitments (Barry *et al.*, 1995). Investment projects yielding greater expected net returns are likely to be positively associated with loan repayment since the borrower has more income to meet both his consumption requirements and debt obligations (Okorie, 1986). However, additional liquidity provided by the loan may flow toward the most attractive use available from the perspective of the borrower. Too much emphasis on the additional funds provided by the loan could be misleading since the borrower might divert funds (fungibility) to some other use more important at the time (von Pischke and Adams, 1980). Vigano (1993) found no relationship between specific project profitability and loan repayment, owing to the fungibility of money. Hence, gross present annual income, which accounted for all sources of borrower income excluding income derived from the new investment, was used to estimate LIQUID. This emphasised total borrower liquidity and not merely liquidity generated by additional income from the project. The higher is LIQUID, the greater is the ability to repay timeously.

The previous use of MFO2 loans by the borrower (PREVLN) is used as a proxy for the extent of the lender-borrower relationship. The lender is likely to have more reliable information on established borrowers, while the borrower has a better knowledge of the lending procedures and late payment penalties imposed by the MFO2 (where the MFO2 does not refinance clients who default on previous loans).

Finally, clients having an established track record with MFO2 are more likely to repay loans than are new borrowers. The GENDER variable is also a potentially important discriminator, and if the past findings amongst rural borrowers that women have a better repayment record than men (Christen *et al.*, 1994) holds, GENDER is likely to be positively related to loan default. The following section discusses data source and sampling methodology.

6.3 Data Sampling for the MFO2 Econometric Model

Two branches of MFO2 – Port Shepstone and Pietermaritzburg, were selected for the analysis as they could provide the most comprehensive information required for the study. Given the relatively small population of medium-term agricultural loans, all observations were included in the study sample to maximise the degrees of freedom required for multiple category response models. A data sheet was compiled to record information extracted from the borrower case files (see Appendix E). Following Aguilera-Alfred and Gonzalez-Vega (1993), repayment performance was monitored over time to avoid distortions in delinquency measurement as a result of different loan maturities and portfolio growth rates. Primary data from individual borrower dossiers were obtained for all medium-term agricultural loans disbursed in 1993 and 1994 (1993/94 data was used as MFO2 has moved away from financing relatively small agribusiness ventures), giving a total population of 59 dossiers.

To account for any possible cash-flow variations arising from the nature of the agricultural activities, the loan repayment categories were defined such that flexibility within a repayment category was accounted for. The repayment status of these loans as at a selected cut-off date of 31 March 1996 was classified into three categories: (1) current or without repayment problems (all instalments due paid within 30 days of the cut-off date), (2) paid with arrears (all instalments due paid within 30 to 90 days of the cut-off date), and (3) in default (any instalments due still unpaid in excess of 90 days after the cut-off date). Given this classification, 29 per cent of the 59 loans were current, 17 per cent were in arrears and 54 per cent were in default. The relatively high default rate may have substantial implications for the financial viability of the agricultural divisions at these two branches. The next section reviews some characteristics of the sample borrowers.

6.4 Characteristics of MFO2 Sample Borrowers at the Port Shepstone and Pietermatitzburg branches

6.4.1 General Characteristics of Port Shepstone and Pietermaritzburg Sample Borrowers

Borrowers were classified in four categories shown in Table 6.2, namely individuals applying for credit (male and female), borrower groups and joint ventures (companies or partnerships). Of the 59 borrowers, 78 per cent were male and 17 per cent female while groups and joint ventures accounted for the small balance. The small percentage of women in the sample receive only 13 per cent of the total volume disbursed, while male borrowers receive the largest share. Average loan sizes reflect a similar trend, except for joint ventures which have the largest average loans.

Table 6.2 Loan Size of MFO2 Medium-term Loans by Type of Borrower, 1996

Borrower Type	Number of Loans		Volume Disbursed	Average Loan Size
	n	%	(Rand)	(Rand)
Male	46	78	1 107 179	24 069
Female	10	17	189 647	18 964
Group	1	2	139 28	13 928
Company/ Partnership	2	3	972 46	48 623
TOTAL	59	100	1 408 000	23 864

Smaller loan sizes for women may be attributed to their smaller businesses, lower levels of collateral and less access to human and material resources as found by Yaron (1992). Table 6.3 shows that women have smaller businesses (lower estimated annual average gross incomes) relative to men and joint ventures. Average annual present income is also considerably smaller for women, indicating an overall lower level of liquidity, possibly due to most of the women being employed in jobs earning a fixed salary, or having small trading businesses.

Table 6.3 Occupations and Incomes of MFO2 Sample Medium-term Loan Borrowers, 1996

Type of Borrower	Present Occupation (n = 57)			Average Annual Present Income	Average Gross Annual Income from Operations
	Agribusiness (%)	Fixed Salary (%)	Trader (%)	(Rand)	(Rand)
Male	53	29	18	50 511	91 152
Female	11	44	44	40 008	76 005
Group	100	0	0	-	86 520
Company/ Partnership	100	0	0	167 400	319 690
TOTAL	47	30	21	52 226	104 126

The joint ventures tended to have the largest loans because they were relatively large businesses with considerable liquidity (large average annual gross income and annual average present income). The two joint ventures were involved in contract cane and timber harvesting and transport. Most of the male borrowers (53 per cent) were involved in agribusiness activities - contract ploughing and transport in the rural areas. Twenty nine per cent of male clients were employed full-time earning a fixed salary, while 18 per cent had trading businesses, usually shops. The size of their businesses was relatively large, and they had higher liquidity than the female borrowers.

Table 6.4 shows that most of the medium-term loans (63 per cent) disbursed were for the purchase of tractors, trailers and ploughs for contract transport and ploughing in the communal areas of KZN, with tractors or a tractor-plough combination being the most common assets financed.

Table 6.4 Investment Activities Financed with MFO2 Medium-term Agricultural Loans, 1996

Investment Type	Number of Loans		Volume of Disbursement		Average Loan Size
	N	%	(Rand)	%	(Rand)
Livestock production	13	22	192 125	14	14 778
Timber/ Sugarcane contractors	6	10	202 038	15	33 673
Maize milling	3	5	31 461	2	10 487
Contract Ploughing and Cartage	36	63	946 206	69	26 283
TOTAL	58	100	1 371 830	100	23 652

The average loan size of R26 283 indicates that most of the equipment purchased tended be second-hand, potentially reducing its reliability and ultimately affecting contractor productivity. Twenty-two per cent of the loans were for livestock production, mostly for the purchase of broiler equipment, feed and day old chickens, with only one loan being for the purchase of cattle. These loans accounted for only 14 percent of the total volume disbursed. Timber and sugar cane harvest and transport activities had relatively large average loan sizes due to the purchase of relatively more expensive necessary equipment, such as lorries. Loans to purchase of hammer mills for maize milling accounted for the lowest number of loan disbursals. Most of the medium-term loans (73 per cent) were thus for the purchase of equipment for contracting activities. This is expected given that part of the mechanisation policy of the SA government's FSP, of which the RFI was the major implementor in KZN, promoted the support of contracting activities in rural areas to facilitate crop production.

Table 6.5 shows that 50 per cent of the women were involved in either livestock production or contract ploughing and harvesting. Sixty-nine per cent of the men had contract ploughing and cartage businesses, with 16 per cent being involved in livestock production (mainly broiler production). The high number of men involved in contract ploughing and cartage can partially be explained by MFO2 having financed tractor equipment purchases for many retrenched miners in the Port Shepstone area who had returned to settle with their families. The only group loan in the sample was for broiler production. The joint ventures (partnerships and companies) were involved in timber and sugarcane contracting. The characteristics of the medium-term loans and some features of the two MFO2 branches are described in section 6.4.2 below.

Table 6.5 Investment Activities by MFO2 Medium-term Loan Borrower Type, 1996

Investment Activities	Male		Female		Group		Partnership / Company	
	n	%	n	%	n	%	n	%
Livestock production	7	16	5	50	1	100	-	-
Timber/ sugarcane contracting	5	11	-	-	-	-	2	100
Maize milling	2	4	1	10	-	-	-	-
Contract ploughing and Cartage	31	69	4	40	-	-	-	-
TOTAL	45	100	10	100	2	100	1	100

6.4.2 Loan and Lender Characteristics of Port Shepstone and Pietermaritzburg Branches

Table 6.6 shows the number and volume of loans disbursed for the Port Shepstone and Pietermaritzburg branches of MFO2. Sixty one per cent by number and 56 per cent by volume were disbursed by the Port Shepstone branch, and only 39 per cent by number and 44 per cent by volume by the Pietermaritzburg branch. The high percentage of loans in the Port Shepstone area is due to the FSP being implemented in this region which resulted in MFO2 giving particular focus in terms of loan disbursal to this area. While the Port Shepstone Branch had more disbursals, the Pietermaritzburg branch, on average, disbursed larger loans.

Table 6.6 Number, Amount and Average MFO2 Medium-term Loan Size, 1996

Regions	No. of Loans		Volume Disbursed		Average Loan Size
	n	%	Rand	%	(Rand)
Port Shepstone	36	61	794776	56	22077
Pietermaritzburg	23	39	613225	44	26661
TOTAL	59	100	1408000	100	23864

In Table 6.7 loans to contractors clearly accounted for most of the disbursals by number and volume for the Port Shepstone branch. Loans for livestock (predominantly broiler) production and timber and sugarcane contracting accounted for 42 per cent of the volume, and loans for contracting ventures for 58 percent disbursed for the Pietermaritzburg branch. Timber and cane cartage on a large scale was more prevalent in the Pietermaritzburg area with relatively large loans being disbursed to timber and sugarcane contractors.

Table 6.7 Activities Financed by the two MFO2 branches, 1996

Activities Financed	**Port Shepstone**		**Pietermaritzburg**	
	number of loans	% by volume of loans disbursed	number of loans	% by volume of loans disbursed
Livestock production	8	9	5	20
Timber/ Sugarcane contractors	2	9	4	22
Maize Milling	3	4	0	0
Contract Ploughing and Cartage	22	78	14	58
TOTAL	35	100	23	100

Table 6.8 shows that most of the loans for the Port Shepstone branch were five year loans for equipment purchase (mainly tractors and ploughs for contract ploughing and cartage) with 40 per cent of the loans ranging from R35 000 to R45 000. Crosby (1995) noted that loans of about R50000 would place great financial stress on contractors even with concessional interest rates in rural areas where work was highly seasonal and erratic. The livestock production (day-old chick, feed and equipment purchase) and maize milling loans of the Port Shepstone branch were relatively small, most being one to three year loans. Fifty per cent of the equipment purchase

loans at the Pietermaritzburg branch were relatively smaller, ranging from R15 000 to R25 000 with loan terms of five years.

Table 6.8 Loan Terms and Loan Sizes by MFO2 Branch, 1996

Loan Term (years)	**Investment Activities**							
	Livestock Production		Timber/ Sugarcane Contracting		Maize Milling		Contract Ploughing and Cartage	
	% PSH[a] n = 8	% PMB[b] n = 5	% PSH n = 2	% PMB n = 4	% PSH n = 3	% PMB	% PSH n=22	% PMB n = 14
1 – 3	100	20	50	25	100	-	19	21
3 – 5	-	20	-	75	-	-	9	29
5 – 6	-	-	50	-	-	-	72	43
6 – 7	-	60	-	-	-	-	-	7
TOTAL	100	100	100	100	100	-	100	100
Loan Size Range								
< R10 000	63	-	50	25	33	-	14	7
R10 000 R14 999	25	40	-	25	64	-	5	7
R15 000 - R24 999	12	40	-	-	-	-	14	50
R25 000 - R24 999	-	-	-	25	-	-	27	22
R35 000 - R45 000	-	-	-	-	-	-	40	-
> R45 000	-	20	50	25	-	-	-	14
TOTAL	100	100	100	100	100	-	100	100

Note: [a] PSH = Port Shepstone, [b] PMB = Pietermaritzburg

More emphasis seems to be given to timber and sugarcane transport and harvest contractors, and broiler production, at the Pietermaritzburg branch. Pietermaritzburg also had some large loans over R45 000 for livestock, timber/ sugarcane and plough contracting. According to Table 6.9, the average loan approval times and grace periods allowed by the two branches varied, with the Port Shepstone branch having shorter average loan approval times and grace periods before the first instalment was required.

Table 6.9 Loan Approval Times and Grace Periods for Investment Activities by MFO2 Branch, 1996

Investment Activities	Port Shepstone		Pietermaritzburg	
	Average Loan Approval Times			
	n	Average number of days	n	Average number of days
Livestock production	8	26	4	55
Timber/ Sugarcane contracting	2	28	4	44
Contract milling	3	24	0	0
Contract Ploughing and Cartage	22	35	14	75
TOTAL	35	32	22	65
	Average Grace Period			
Livestock production	8	88	4	104
Timber/ Sugarcane contracting	2	43	3	54
Contract milling	3	73	0	0
Contract Ploughing and Cartage	21	78	14	87
TOTAL	34	78	21	86

Loan approval times are, on average, one month longer for the Pietermaritzburg branch. Pietermaritzburg has disbursed, on average, larger loans than Port Shepstone, with four loans above R45 000, which do require more information resulting in longer loan approval times. However, this requirement may not be the only reason for longer loan approval time at Pietermaritzburg. Loan approval times for tractor, trailer or plough purchases differed considerably between the two branches even though 50 per cent of these loans had much lower loan size ranges than the Port Sheptsone branch. Delays at local tractor dealerships, long travelling distances for borrowers, and administrative procedures may have also lengthened loan approval times. While assessing borrower repayment capacity is important, timely disbursal of loans is crucial for plough and cartage contractors, as long waiting periods may jeopardise their income-generating capability. The next section briefly describes loan default status for the sample borrowers.

6.4.3 Loan Default Status of Port Shepstone and Pietermaritzburg Sample Borrowers

Only 29 per cent of the 59 borrowers were classified as current, 17 per cent were in arrears, and most (54%) were in default. The high default rates seem unacceptably high and may impose considerable financial stress of the agricultural lending programmes at these two branches. In Table 6.10, 54 per cent of borrowers accounting for 46 per cent of the value of the loans disbursed were in full default. This is a substantial portion of medium-term loan portfolios for the two branches, and negatively affects their financial viability and reductions in subsidy dependence. Female borrowers and group loans accounted for the highest number and percentage value of loans in default. Fifty percent of male borrowers, accounting for 40 per cent of the value of loans disbursed, were in default. In contrast, 70 per cent of the number of loans accounting for 86 per cent of the amount disbursed to women were in default. Hunte (1993) found similar results for repayment performance at GAIBANK in Guyana. Although the result may be sample specific, this runs contrary to the hypothesis that female borrowers are likely to have lower default levels.

Table 6.10 Repayment Status of MFO2 Sample Medium-term Loans by Type of Borrower, 1996

Borrower Type	Total Volume Disbursed (Rand)	Current (Rand)	%	Repaid with Arrears (Rand)	%	Default (Rand)	%
Male	1107179	303983	27	370396	33	432800	40
Female	189647	15372	8	10768	6	163507	86
Group	13928	-	-	-	-	13928	100
Partnership/ Company	97246	61750	63	-	-	35496	37
TOTAL	1408000	381105	27	381164	27	645731	46
	Total Number Disbursed	n	%	n	%	n	%
Male	46	14	30	9	20	23	50
Female	10	2	20	1	10	7	70
Group	1	-	-	-	-	1	100
Partnership/ Company	2	1	50	-	-	1	50
TOTAL	59	17	29	10	17	32	54

Repayment status by investment activity in Table 6.11 indicates that 69 per cent of the number of loans, accounting for 59 per cent of the value of loans disbursed for livestock production were in default. Fifty-six per cent of the number of loans, accounting for 49 per cent of the value of loans disbursed to borrowers with contract harvesting and ploughing activities, were in default. Broiler production and contract ploughing and cartage thus together accounted for most of the defaulting loans both in number and by value of loans disbursed. Maize milling and timber and sugarcane contract harvesting and carting accounted for the greatest number and value of loans being current. Twenty-two per cent of the number of loans, or 30 per cent of the value of loans disbursed to contract ploughing and cartage, were in arrears. One loan for timber and contracting activities accounted for 42 per cent of the value of the loans disbursed to timber and sugarcane contracting activities. It appears, therefore, that relatively few borrowers with large loans aimed at contracting activities constituted the arrears category.

Table 6.11 Repayment Status of MFO2 Sample Medium-term Loans by Investment Activity, 1996

Investment Activity	Total Volume Disbursed	Current		Repaid with Arrears		Default	
	(Rand)	(Rand)	%	(Rand)	%	(Rand)	%
Livestock Production	192 125	68 809	36	10 768	6	112 548	59
Timber/ Sugarcane Contracting	202 038	85 738	42	84 400	42	31 900	16
Maize Milling	31 461	31 461	100				
Contract Plough and Cartage	946 206	195 097	21	285 996	30	465 119	49
TOTAL	1 371 830	381 105	28	381 164	28	609 561	44
	Total Number Disbursed	n	%	n	%	n	%
Livestock Production	13	3	23	1	8	9	69
Timber/ Sugarcane Contracting	6	3	50	1		2	33
Maize Milling	3	3	100		17		
Contract Plough and Cartage	36	8	22	8	22	20	56
TOTAL	58	17	29	10	17	31	54

According to Table 6.12 male borrowers who were current on loan repayments had a higher own equity contribution relative to loan size than male borrowers who were in arrears and in default. This also held for female borrowers. No equity contribution was required by the defaulting joint liability group, while only a small equity contribution was required from one joint venture group.

This is probably because these joint ventures (partnerships and companies) had substantial asset bases that could be used as collateral in the place of own equity.

Table 6.12 Repayment Status by MFO2 Borrower's Own Equity Contribution Relative to Medium-term Loan Size, 1996

Borrower Type	Average Relative Own Equity Contributions (%)					
	Current		Arrears		Default	
	n	%	n	%	n	%
Male	14	21	9	14	23	16
Female	2	19	1	20	7	14
Group	-	-	-	-	1	0
Partnership/ Company	1	5	-	-	1	0
TOTAL	17	20	10	15	32	14

Although MFO2 had rules on relative own equity contribution requirements, these were not always strictly adhered to, depending on the merits of the individual loan application. The general trend in Table 6.12 is that borrowers with higher own equity contributions tend to be current rather than in default or in arrears. A higher own equity contribution provides a greater incentive for borrowers to exert effort to try and ensure investment success, resulting in improved ability to repay the loan.

Borrowers' liquidity as proxied by present annual income at the time of the loan application (which includes all sources of borrower income) is, on average, higher for borrowers who are current than for borrowers who are in default. Table 6.13 shows that borrowers in arrears are an exception since average annual present income was higher than for borrowers who were current. A few borrowers in arrears were granted relatively large loans. Given that loan size is a function of repayment capacity and liquidity, the large average annual present income for borrowers in arrears is expected.

Table 6.13 Repayment Status by MFO2 Sample Borrower Liquidity Levels, 1996

Borrower Type	Total Present Income	Average Annual Present Income (n = 58)					
		Current		Arrears		Default	
	(Rand)	n	(Rand)	n	(Rand)	n	(Rand)
Male	2 489 025	14	57 621	9	98 093	23	34 760
Female	369 080	2	27 180	1	124 000	6	31 786
Group*	-	-	-	-	-	1	0-
Partnership/ Company**	334 800	1	334 800	-	-	1	0
TOTAL	3 192 905	17	70 344	10	100 684	31	31 941

Female borrowers, on average, have lower annual present incomes than men. Many of the women had fixed employment and other business activities so their, experience in, and appropriate supervision of, contracting businesses may have been lacking. The joint ventures have the largest average annual present incomes as expected. Overall, borrowers with better liquidity had better repayment ability, except for those borrowers in arrears.

Some 58 percent of all medium-term loans disbursed by the Port Shepstone branch, were in default, 17 percent in arrears and 25 per cent current. Table 6.14 indicates that these amounted to 54, 19 and 27 per cent of the value of the loans, respectively. The situation for Pietermaritzburg was more favourable, with 48 per cent of all medium-term loans disbursed, accounting for 35 per cent by value, being in default.

Table 6.14 Repayment Status of MFO2 Sample Medium-term Loan Borrowers by Branch, 1996

Region	Total Volume Disbursed	Current		Repaid with Arrears		Default	
	(Rand)	(Rand)	%	(Rand)	%	(Rand)	%
Port Shepstone	794 776	213 480	27	148 812	19	432 484	54
Pietermaritzburg	613 224	167 625	27	232 352	38	213 247	35
TOTAL	1 408 000	381 105	27	381 164	27	645 731	46
	Total No. Disbursed	N	%	n	%	N	%
Port Shepstone	36	9	25	6	17	21	58
Pietermaritzburg	23	8	35	4	17	11	48
TOTAL	59	17	29	10	17	32	54
Average Loan Size		Rand		Rand		Rand	
Port Shepstone		23 720		24 802		20 594	
Pietermaritzburg		20 953		58 088		19 386	
TOTAL		22 417		381 16		201 79	

About 35 per cent of the Pietermaritzburg medium-term loans, accounting for 27 per cent by value, were current, and only 17 per cent, accounting for 38 per cent by value, were in arrears. It appears, therefore, that the large loans disbursed by the Pietermaritzburg branch for broiler production, timber and sugarcane contracting and contract ploughing and cartage were in distress. While the trend appears to be that borrowers with larger average loans tend to be current, some borrowers with particularly large loans for sugarcane and timber contracting, and broiler production in the Pietermaritzburg area have repayment problems.

Borrowers with repayment problems thus tend to be those that have invested in livestock production (mainly broiler production) and contract ploughing and cartage activities that have lower liquidity and made lower own equity contributions. Contrary to expectations, women in this sample have the poorer repayment records. This is possibly due to the lower levels of liquidity and the smaller size of the business ventures which are more prone to negative income shocks. Borrowers with larger loans tend, on average, to have better repayment records (loan size is a proxy for asset base, income and level of diversification). The next sections will present the econometric model used to estimate factors influencing loan default of MFO2 sample borrowers.

6.5 Econometric Methods to Estimate the Economic Model for MFO2

Since the single equation models have been presented in section 5.7, these will not be repeated here. However, the dependent variable for the MFO2 loan default model is extended to three discrete categories. For situations where the data are individual specific involving more than two discrete categories in the dependent variable, the unordered multinomial logistic regression model first developed by Theil (1969) can be used. The maximum likelihood estimation of regression models with multiple dependent variables is discussed by Greene (2000) and Maddala (1983). Given that P_j ($j = 1,..,3$) are the probabilities of each one of the three repayment categories occurring, the multinomial logit model can be expressed as:

$$\ln\left(\frac{P_j}{P_1}\right) = \beta_{0j} + \beta_{1j}X_{1i} + ... + \beta_{kj}X_{ki} + \mu_{ji} \tag{6.1}$$

for $j = 2,3$; $i = 1,...,n$; and $k = 1,...,K$

where P_1 is the probability of loans being current, P_2 of loans being in arrears and P_3 of loans in default. The X_{ki} are vectors of explanatory variables, β_{kj} are estimated parameters, n is the number of observations and k the number of explanatory variables. From equation (6.1) the log odds ratios $\ln(P_2 / P_1)$, $\ln(P_3 / P_1)$ and $\ln(P_3 / P_2)$ can be computed, where $\ln(P_3 / P_2)$ is $\ln(P_3 / P_1) - \ln(P_2 / P_1)$.

The probabilities of the three category response model must sum to one, which requires a normalisation procedure such that one category serves as the base category to which all other categories are compared. Aldrich and Nelson (1984) and Greene (1990) show that, as a result of the normalisation procedure, the sign of the parameter estimates is in the same direction as the change in the log odds ratio for an increase in X_i, but not necessarily when estimating the change in probabilities. Hence, parameter estimates should be interpreted with caution.

In addition, the parameter estimates become unstable, and probabilities under-classified where dependent variable categories are small relative to the other categories, limiting the classification power of the model (Hosmer and Lemeshow, 1989; Greene, 1990). This, and the fact that the number of parameters proliferates as the number of discrete dependent categories increases, requires relatively large numbers of observations per category for the model to give stable parameter estimates and have good predictive power (Aldrich and Nelson, 1984; Hosmer and Lemeshow, 1989). The small number of observations for category two in the sample data may thus lead to unstable parameter estimates and poor classification results for this category. The following section presents the results of the estimated logit models.

6.6 Logit Model Results

Two types logistic regression models estimated included the binomial and the unordered multinomial response models. While the logistic regression model is fairly robust one critical assumption of the model, similar to linear regression analysis, is that no linear relationships exist amongst the independent variables (Aldrich and Nelson, 1984). This may lead to large variances and co-variances making precise parameter estimation difficult, leading to an increase in Type II (false acceptance of null-hypothesis) errors. Several methods may be used to detect multicollinearity, with bivariate correlation coefficient and condition indices being used in this study (Gujarati, 1995). Prior to reviewing the correlation matrix, the variable abbreviations and descriptions as used in the statistical models are given below.

Loan Characteristics

LSIZE = Loan principal amount (Rands).

OWNLN = borrower's direct equity contribution relative to loan size.

Business Characteristics

CONTRACT = 1 if the borrower funded a chicken production or contract ploughing and cartage business venture, and 0 if the borrower funded a maize milling or timber/sugar-cane contract harvesting and transport business.

LIQUID = present annual income relative to annual debt obligations.

Personal Characteristics

PREVLN = 1 if the borrower has had previous loans with the RFI, and 0 if a first time borrower.

GENDER = 1 for male borrowers, and 0 for female borrowers.

The bivariate correlations of the independent variables used in the models are given in Table 6.15 below. Some multicollinearity exists between LSIZE, OWNLN and LIQUID, with bivariate correlation coefficients being greater than 0,25 and statistically significant at the five per cent level. The variables LIQUID and PREVLN are also positively correlated, with a correlation coefficient of 0.4041. While bivariate correlations indicate the presence of multicollinearity, they are considered unreliable, particularly in models with more than two explanatory variables (Gujarati, 1995). An alternative test for multicollinearity, as suggested by Gujarati (1995) and Greene (1990), is to use a condition index as shown in Table 6.16.

Table 6.15 Bivariate Correlation Coefficients of the Independent Variables in the MFO2 Medium-term Loan Default Model

Variable	LSIZE	OWNLN	CONTRACT	LIQUID	PREVLN	GENDER
LSIZE	1.0000	-0.2821**	-0.0547	-0.2611**	-0.0933	0.1313
OWNLN	-0.2821**	1.0000	-0.1166	0.1166	-0.2671**	0.0017
CONTRACT	-0.0547	-0.1166	1.0000	-0.2501	0.0235	-0.0732
LIQUID	-0.2611**	0.1166	-0.2501	1.0000	0.4041***	0.0020
PREVLN	-0.0933	-0.2671**	0.0235	0.4041***	1.0000	-0.0583
GENDER	0.1313	0.0017	-0.0732	0.0020	-0.0583	1.0000

Note: ** and *** - indicate significance at the 5% and 1% levels, respectively

The condition index is the square root of the ratio of the largest and smallest characteristic root. Condition indices of between 10 and 30 indicate moderate to strong multicollinearity. The highest condition index for the sample data was 11.927, which indicates moderate collinearity, with PRINC, OWN, LIVCON, and PREVLN contributing to the collinearity as reflected by the relatively high variance proportions (Gujarati, 1995; Greene, 1990).

Table 6.16 Condition Indices for the Independent Variables in the MFO2 Medium-term Loan default Model

Eigenvalue	Condition Index	Variance Proportions						
		Constant	PRINC	OWN	LIVCON	DEBTCOV	PREVLN	GENDER
4.830	1.000	0.002	0.008	0.007	0.005	0.009	0.008	0.006
0.963	2.241	0.001	0.022	0.008	0.004	0.156	0.280	0.004
0.543	2.983	0.000	0.080	0.105	0.006	0.253	0.268	0.000
0.3001	4.008	0.007	0.366	0.113	0.072	0.296	0.145	0.006
0.173	5.288	0.001	0.187	0.508	0.236	0.118	0.230	0.085
0.158	5.521	0.001	0.102	0.000	0.195	0.102	0.045	0.721
0.034	11.927	0.995	0.236	0.259	0.481	0.068	0.242	0.178

Since only mild collinearity is present no remedial measures were taken. Additional data were not available, while ridge regression techniques make the interpretation of the results ambiguous (Greene, 1990) and dropping an explanatory variable may cause specification bias.

6.6.1 Binomial Logit Model

For the binomial logit model, the current and arrears categories were combined to form a less stringent category where borrowers are defined as current if all instalments due had been paid within 90 days of the cut-off date. Given the variability of cash flows for contracting ventures, MFO2 borrowers often repaid large amounts when cash flows permitted. For the binomial logit model estimated in Table 6.17 the residual deviance of 60.864 has a chi-squared distribution with 50 degrees of freedom and shows no significant lack of fit of the overall model. Collet (1991) and Hosmer and Lemeshow (1989) show that the residual deviance is an unreliable estimator of goodness of fit when the number of possible combinations in the independent variables approximately equals the number of observations which occurs when continuous variables are present in the model.

Hosmer and Lemeshow (1989) propose the use of the score statistic that follows a chi-squared distribution which has an advantage over the residual deviance when there are continuous variables in the model. The score statistic of 61.072 with 50 degrees of freedom also shows no significant lack of fit. The overall model chi-square of 17.997 implies that the six variables in the model contribute significantly toward predicting $P(Y = 1)$ and the null hypotheses $H_0 : \beta_1 = \beta_2 = \beta_k = 0$ is thus rejected, indicating that the variability observed in the data is not merely due to sampling variation.

The statistical significance of individual parameters in the model is most accurately measured by the likelihood ratio test which follows a chi-squared distribution with one degree of freedom (Aldrich and Nelson, 1984; Hosmer and Lemeshow, 1989; Menard, 1995). According to Table 6.17, the parameter estimates for LSIZE, OWNLN, CONTRACT and LIQUID are statistically significant at the five per cent level of probability. The variables PREVLN and GENDER contribute little towards the explanatory power of the model. The Wald statistic which follows a standard normal distribution may also be used to test the significance of individual parameter estimates. Aldrich and Nelson (1984) recommend the use of the more conservative t-values to measure statistical significance of the individual parameter estimates. The disadvantage of the Wald statistic is that for large coefficients the standard error is inflated which may lead to false acceptance of the H_0: $\beta_k = 0$ (Menard, 1995). Again, the parameter estimates for LSIZE, OWLN, CONTRACT and LIQUID are significant at the 1%, 10% and 15% levels, respectively.

Table 6.17 Parameter Estimates of the Binomial Logit Model

Variable Name	$\ln(P_1/1 - P_1)$	Likelihood Ratio Test (χ^2 distribution)
CONSTANT	3.1485	
LSIZE	-0.000075^{***} (-2.474)	3.478^{**}
OWNLN	-7.0460^{*} (-1.72)	3.816^{**}
CONTRACT	$1.5698^{15\%}$ (1.52)	3.743^{**}
LIQUID	$-0.0666^{15\%}$ (-1.44)	4.428^{**}
PREVLN	-1.0077 (-1.17)	1.123
GENDER	-0.8866 (-1.04)	1.139
	Overall model chi-square	17.997^{***}
		Residual deviance = 60.864

Score statistic = 61.072
Overall correct classification = 75.44%
Correctly classified as current = 77.78%
Correctly classified as default = 73.33%

Note: *, **, *** indicate significance at the 10%, 5% and 1% levels respectively

The model correctly classifies 75 per cent of the sample borrowers - 78 per cent of current and 73 per cent of default loans. The ability of the model to classify borrowers correctly may also be used as a goodness of fit measure. The signs of the estimated coefficients mostly agree with *a priori* expectations. For lending policy purposes, smaller loans and own equity contributions, contracting and broiler production ventures, as well as, lower liquidity, are key factors associated with borrowers being in default (instalments paid or unpaid 90 days after the cut-off date). The negative sign for GENDER, indicating that female borrowers are more likely to default than male borrowers, is expected (female borrowers had repayment problems in the sample). This may be a sample-specific result or may reflect the nature of the women borrowers' businesses, with most going into broiler production or contract ploughing and cartage. Given that the average loan size of loans used by women was substantially lower than that of men, women may be operating smaller businesses or, in the case of contracting, buying cheaper second-hand tractors which are less reliable and have greater down-time (and thus present greater cash flow problems). In addition, the women may have less experience and less time to commit themselves to their contracting businesses.

Borrowers with larger loan sizes have better repayment capacities with the log-odds in favour of loan default being negative for LSIZE. Given that loan size proxies business size and borrower wealth, borrowers with larger loans tended to have larger estimated gross incomes, better liquidity and larger, possibly better diversified asset bases. This enables them to better withstand negative income shocks and divert less business funds to personal consumption, thereby improving loan repayment capacity (Barham *et al.*, 1996). Larger borrowers in the sample also tended to have well-established markets for their products and services. In addition, their relatively larger asset bases provided more verifiable collateral to lenders, better information on potential investment returns, and reduced the cost per unit of credit lent. Ortmann and Lyne (1995) also found that borrowers in rural KZN who generated cash from sales in excess of family consumption needs had better loan repayment capacities.

Borrowers with higher own equity contributions had a lower probability of default relative to borrowers with lower equity contributions. Greater own contributions increased the borrower's stake in the business, thus inducing more effort to ensure business success. In addition, higher own equity contributions tended to be associated with lower loan approval times since the information requirement by the lender was lower. Loans for contracting and broiler production also significantly contributed to borrowers being in default. Contractors will be successful if they have good management skills and are financially sound. This implies achieving some target level of profit margin, affordable equipment, good cash flow, charging realistic tariffs and having sufficient work (which requires good scheduling). In addition, the equipment must be technically appropriate, non-productive hours in peak periods must be minimised and maintenance of the equipment must be good (Crosby, 1995). Research on FSP contractors by Crosby (1995) shows that individuals entering into contracting ventures often did not have farm backgrounds and, therefore, often did not provide satisfactory work. They were also not well-diversified, and focused only on one activity, mainly ploughing.

These factors together with the erratic demands of contract ploughing services peaking at planting periods and down-time due to old, unreliable equipment, may induce cash flow problems. Ortmann and Lyne (1995) found that contractors in KZN, specifically in the FSP areas, had problems in accessing fuel with poor roads, lack of maintenance services, clients not paying their debts and too little work contributing to poor cash flows. Given these problems, Crosby (1995) estimates that individuals would experience loan repayment difficulty if loans for equipment exceed of R10 000. Poor working conditions and the relatively large loan sizes of the sample borrowers, together with the inexperience of many MFO2 borrowers returning from the mines, may explain the poor performance of the MFO2 sample contracting loans.

Broiler production ventures also require skilled management and supervision. Increased competition due to the lowering of tariffs, and an outbreak of Newcastle disease at the time of the survey, induced cash flow problems for these borrowers, reducing repayment capacities. Borrowers with greater liquidity (ratio of all present income to annual debt obligations), had higher odds of repaying their loans (negative LIQUID coefficient). Ensuring sufficient liquidity is vital since the additional income of the loan may not necessarily be used for repaying the loan but may be diverted to some other use more important at the time. While the contracting ventures mostly had relatively high estimated gross incomes, most borrowers entering into these ventures defaulted. Aguilera-Alfred and Gonzalez-Vega (1993) emphasised that loans repaid in arrears can markedly affect MFI liquidity and viability. The binomial logit model was, therefore, extended to include an arrears category, and replaced by a multiple category response logit model described in section 6.6.2.

6.6.2 Unordered Multinomial Logit Model

The unordered multinomial logit model estimated in Table 6.18 had a residual deviance of 83.17 and a chi-squared distribution with 43 degrees of freedom and shows a significant lack of fit. This is substantiated by the score statistics of the two individual base category regressions (P_2/P_1) and (P_3/P_1) which are 24.26 and 52.83 with 21 and 31 degrees of freedom respectively. The overall likelihood ratio test is highly statistically significant indicating that the variables included in the model have significant explanatory power with the variability observed not merely being due to sampling variation (Menard, 1995). The lack of fit may be due to the small number of observations in category two (arrears) and the definition of the three categories.

Table 6.18 Parameter Estimates of the Unordered Multinomial Logit Model

Variable Name	$Ln(P_2/P_1)$	$ln(P_3/P_1)$	$ln(P_3/P_2)$	Likelihood Ratio Test (χ^2 distribution)
Constant	-5.56479 (-1.29)	3.79416 (1.72)	9.35895 (2.61)	
LSIZE	0.00009* (1.81)	-0.00005 [15%] (-1.53)	-0.00014*** (-2.83)	7.9134***
OWNLN	-1.36906 (-0.23)	-9.03642** (-1.93)	-7.66736 (-1.21)	3.8795 [15%]
CONTRACT	4.28042* (1.79)	1.77329* (1.72)	-2.50713 (-0.99)	5.7980**
LIQUID	0.09409 [15%] (1.54)	-0.02526 (-0.50)	-0.11935*** (-2.07)	3.9638 [15%]
PREVLN	-1.88467 (-1.31)	-2.01593** (-1.92)	-0.13126 (-0.10)	4.0011 [15%]
GENDER	-1.56856 (-1.08)	-1.53728 (-1.20)	0.03128 (0.02)	1.5303
			Overall χ^2	31.2855
			Residual deviance = 83.17	

Score statistic P_2/P_1 = 24.26 (df = 21)
Score statistic P_3/P_1 = 52.83 (df = 31)
Overall correct classification = 70.18%
Correctly classified current = 58.82%
Correctly classified in arrears = 30%
Correctly classified as defaulters = 90%

Note: *, **, *** indicate significance at the 10%, 5% and 1% levels respectively

Significance of the individual parameters as given by the likelihood ratio test, which now follows a chi-squared distribution with two degrees of freedom, showing that LSIZE and CONTRACT contribute most to the explanatory power of the model. Parameter estimates for OWNLN, LIQUID and PREVLN are statistically significant only at the 15 per cent level. The model correctly classifies 70 per cent of the sample borrowers - 59 per cent of current, 30 per cent of arrears, and 90 per cent of default borrowers. The poor classification results for the current and arrears categories is due to the small size of these categories in relation to the default category. Individuals falling in the border-line cases in the arrears and current categories will tend to be mis-classified, while the default category will tend to be classified relatively well. This is a particular disadvantage of the mutlinomial logit model which is sensitive to the size of individual categories. The signs of the estimated coefficients mostly agree with *a priori* expectations. For lending policy purposes, larger loans, contract ploughing and cartage businesses and borrower liquidity are key factors associated with payment in arrears ($\ln(P_2/P_1)$).

Although *a priori* expectations were that borrowers with larger loans would have fewer repayment problems, the positive sign for the LSIZE coefficient is due to two borrowers experiencing temporary repayment problems on large loans issued by the Pietermaritzburg branch. These borrowers also had larger liquidity levels, resulting in a positive sign for the LIQUID coefficient. The small number of observations in the arrears category may have also contributed to the low significance levels of the estimated parameters. The fit for the model may be improved by increasing the number of observations in the model, specifically for the arrears category.

While the broiler production unit may have been affected by Newcastle disease or a reduction in prices due to imports at the time of the study, the sugarcane contractor may not have received payment from the mill or customers leading to a temporary liquidity problem. Given that larger borrowers tended to have better liquidity, the sign of the LIQUID coefficient, although contrary to expectations, is plausible. Borrowers with smaller loans, less liquidity, who enter into contracting ploughing and broiler production ventures and who have had no previous loans from MFO2, have greater odds of defaulting on their loans than being current. These results are similar to those of the binomial logit model. The only parameter that was not statistically significant in the binomial logit model was PREVLN.

Borrowers who had previous loans from MFO2 possibly have better knowledge of its lending procedures and late payment penalties imposed by the lender. The relatively strong correlation between PREVLN and LIQUID may have affected the significance levels of these variables in the regression. Variables increasing the odds of being in arrears relative being in default ($\ln(P_3/P_2)$) are larger loan size and high borrower liquidity. Again this is partially due to the large loans disbursed by the Pietermaritzburg branch which were in arrears. The results, however, still lend support to the argument that larger borrowers with better liquidity and well-diversified asset bases have greater odds of repaying the loans than defaulting.

6.6.3 Application of the Binomial Logit Model Results for Credit Scoring

In practice, lenders may use various approaches to evaluating the credit-worthiness of loan applicants. These may range from highly subjective approaches based on informal scoring methods such as loan officer heuristics (rules-of-thumb that loan officers develop in evaluating loan applications), to detailed statistical models. The major objectives of these approaches is to determine the potential credit risk of borrowers (Barry *et al.*, 1995:185 - 211). While the credit scoring process cannot be reduced completely to an objective scoring procedure, credit scoring models may assist lenders in risk-related loan pricing (interest rate decisions) and in improving the quality of services through faster loan approval times (Turvey, 1991). Credit models should, however, not be used in isolation, as they serve only as a tool in the credit evaluation process.

Credit scoring has several basic steps, the first being to identify several key variables that best distinguish between potential high- and low-credit risk clients. The second step involves assigning appropriate weights to these variables, and the third step entails the computing of the credit score. Finally, based on the credit score, loan applicants can be assigned to one of a few discrete risk classes for the purposes of loan pricing (Barry *et al.*, 1995: 185 - 211). In this study, logit analysis was used to identify the factors influencing default on MFO2 to assign medium-term loan weights to those factors. Given the good fit of the binomial logit model, its results are used to demonstrate the practical application of the analyses for credit scoring processes. Credit scores are determined by computing the log-odds ratio, which is the sum of the estimated parameters multiplied by the vector of explanatory variables. Figure 6.1 plots the credit score versus the cumulative probabilities of default for the sample data based on the binomial logit model results in Table 6.17.

A credit score with the associated probability of default can be computed and matched with the relevant risk class. Loan applicants with scores greater than 1.1 fall in the very high-risk category, while clients with credit scores below -1.1 are in the low-risk category. This means that an intuitive understanding of probabilities is not required by MFO2 loan officers, improving the ease of using of such a technique. While the above example has demonstrated a practical application of the logit analysis for credit scoring purposes, this model serves an example only. Several methodological factors affect the accuracy of credit scoring models and should be considered before adopting such models to screen loan applicants.

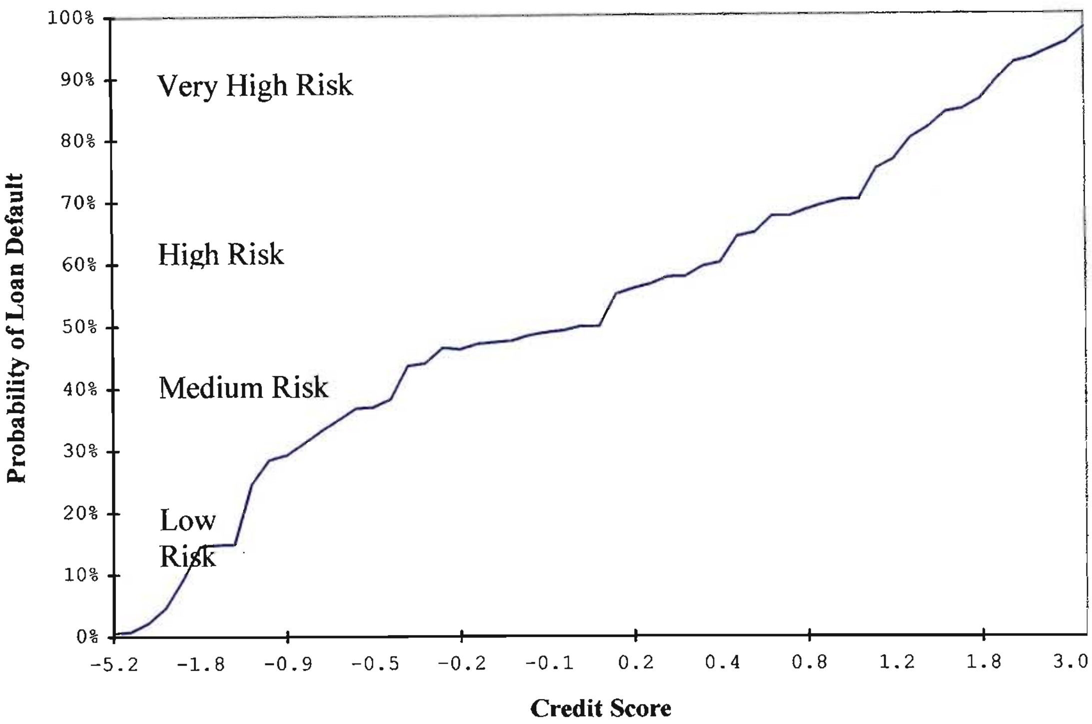

Figure 6.1 Plot of Probability of Default versus MFO2 Client Credit Scores

The first issue is the effect that a non-random sample has on the estimated parameters. The credit scoring decision involves having to discriminate between high- and low-risk loan applicants. Where this decision involves the subjective assessments of loan officers, some rejected individuals might become successful borrowers at other lending institutions, while some accepted loan applicants may prove to be greater credit risks than previously expected (adverse selection and moral hazard problems).

It is also clear that in order to develop an objective credit scoring model, information on both accepted *and* rejected applicants is required. Data on rejected loan applicants were not available for this study. Including only data on existing loan applicants may systematically bias the sample

(Boyes *et al.*, 1989; Miller and LaDue, 1991). While Reichert *et al* (1983) show that the bias as a result of excluding rejected loan applicants may be small, data on rejected loan applicants should be included. The second issue concerns the estimation of the cut-off points which, for Figure 6.1, have been set at the 25, 50 and 75 per cent probabilities of default. A more rigorous estimation of the cut-off points is required, and can be based on both the prior probability of being in a class, and the costs of correct and incorrect classification (Reichert *et al.*, 1983; Miller and LaDue, 1991; Mortensen *et al.*, 1988). This is particularly important where the lender's revenues from, and costs of, correct and incorrect classification are not equal. More information on these costs and revenues of problem and successful loans is required. Such data were not available for this study.

The last issue is the evaluation of the classification ability of the model. To correct for the problem of over-fitting the data set, an independent hold-out sample should be used to validate the results (Miller and LaDue, 1991; Reichert *et al.*, 1983). The relatively small sample size available in this study was not conducive to such a validation technique. Credit scoring models, therefore, require relatively large sample sizes to improve on the accuracy of the scoring model and to facilitate the use of validation techniques which require a hold-out sample. Classification efficiency rates should also be tested to ensure that the estimated scoring model has a better classification ability than the naive model (Miller and LaDue, 1991). The next section discusses the policy implications and conclusions drawn from the evaluation of financial technologies used by the four KZN MFOs, and from the empirical models of credit rationing and loan default for MFO1 and MFO2.

CONCLUSIONS AND POLICY IMPLICATIONS

Financial technologies directly affect the level of outreach and financial self-sustainability achieved over time by the four study MFOs. Key factors that influence the financial technologies are both endogenous and exogenous to the financial institutions. Lenders MFO1 and MFO3 achieved relatively high levels of outreach in terms of the number of clients serviced and the depth of outreach (proxied by average loan size). Lender MFO2 has changed the focus of its target market, while MFO4 has encountered severe financial difficulties. Each of the four MFOs focused on a unique target market: MFO1 and MFO4 financed small loans to low-income households and business groups, while MFO2 and MFO3 finance agricultural loans.

The ability of these financial institutions to improve access to financial services was firstly affected by the organizational mission statement and resolve to service a particular market niche and become self-sustainable. The leaders of MFO1 were committed to providing credit to formally employed low-income individuals on a profitable basis with the intention of also beginning to offer savings facilities. The capacity to do this existed because of the financial backing from MFO1's parent company and the technical expertise within the organisation. Over time, MFO1 staff has accumulated the expertise to service its market and had developed a well-established branch infrastructure for providing financial services. This infrastructure can be leveraged to provide additional services such as savings. The lesson is that sound management and administrative processes, together with technical expertise, require attention if policy makers want to facilitate growth of the microfinance sector in South Africa (SA).

Lender MFO2's mission to improve its financial viability resulted in a shift towards providing larger, more cost-effective loans. Small agricultural loans were costly to administer and exposed MFO2 to relatively high default rates. Since agricultural loans are relatively large by nature, it is not always possible to charge interest rates that cover the costs of lending due to Usury Act restrictions. The lesson is that for SMMEs and the small farming sector, policy makers need to focus on developing the income-generating capacity of these sectors rather than solving liquidity constraints with additional credit. Although MFO4 wanted to be financially viable, funding and administrative constraints severely limited this prospect.

Disorganised senior management and lack of clear direction and focus were part of the problem, while an inadequate management information system (MIS) and lack of adherence to policy and procedure caused the failure of MFO4. The inability to leverage sufficient funds may also have constrained MFO4's expansion. This highlights the limitations of donor funds and the importance of MFOs being able to leverage funds acquired in capital markets or through savings. In order to attract private investment, there must be some evidence of profitability and clients must trust the organisation.

Lender MFO1 reached large numbers of low-income individuals because of the type of financial products it offered and its administrative capacity within the branch network and between the branches and head office. A well-established branch network reduced borrower transaction costs to access credit. Decentralized decision-making allowed for fast loan approval times, as loans were disbursed in cash within one to two hours of the application. Appropriate policies and procedures were also in place to monitor the activities of the branches and cash handling facilities that are administratively expensive and require an MIS that can track the flow of cash in branches. The lack of this type of technology was one of the main constraints faced by both MFO3 and MFO4.

In order to try and save costs and retain administrative control, MFO4 branches did not keep cash. This meant that loans could not be paid out immediately, and that borrowers had to cash cheques at a commercial bank. This, together with a limited branch network, increased borrower transaction costs, while the lack of cash handling at MFO4 also meant that no payments could be received. Deposits had to made at the commercial bank and the deposit slip taken to the branch. Lender MFO3 also did not have cash handling facilities and relied on the administrative capacity of staff at the sugar mills to deal with loan disbursals and loan collections. While such technologies may be cost-saving to the lender, they are necessarily cost increasing to the borrower. Donors may view this as a cost effective option to provide financial services.

However, the MFO needs to offer quality service so that clients derive value from transacting with the financial institution over time. Borrowers must be able to transact fairly easily at the branches to reduce their transaction costs and to encourage repeat borrowing. Agency relationships such as those used by MFO3 with sugar mills can work, but as MFO3 discovered, they can result in longer loan approval times and reduced customer service. At MFO1, MFO2 and MFO4, the borrowers dealt with lender staff in their home language. Borrowers were also not compelled to complete a loan application form - this was done for them by a customer consultant at MFO1 and MFO3, and by loan officers at MFO4. This is important when dealing with individuals that have a high level of illiteracy. Lenders MFO2 and MFO3 had relatively long loan approval times because of fairly centralized decision-making processes, and MFO3 also had to contend with administration by mill personnel. Although the loans may be necessarily more complex, this is an aspect that both of these MFOs can improve (MFO3 has only recently started to place its own staff at the mills in order to reduce the loan processing times).

Lender MFO1 had a custom-built MIS that was optimized for transactional speed and day-to-day management. Data on customers was stored but regularly over-written, while little historic loan performance information was kept. This made it difficult to conduct performance and trend analysis, and to develop a credit scoring system. The MIS, did, however, enable MFO1 to fully transact at branch level and to replicate this technology fairly easily so that rapid branch expansion was possible. Such a system is vital to improve customer service and handle large volumes of cash at branch level. MFO1 has now implemented a data "warehouse" to facilitate this process. Another key issue for an MIS is the extent to which it can be adapted to accommodate savings information. Lender MFO1 has since conducted an expensive programming exercise to incorporate the ability to take savings into the MIS. This meant a considerable time lag from when management took the decision to experiment with savings mobilization and the point when this could be implemented. It thus takes funds, experience and time to develop a well-functioning MIS – 12 years in the case of MFO1.

The absence of a well-functioning, fully transactional MIS seemed to be a constraint for both MFO3 and MFO4. This prevented MFO4 from managing cash at the branch level and also from effectively monitoring its debtors' book. Administrative efficiency and debt management were compromised, and key information about debtors that could be used to develop new products and adjust the loan technology to better cope with adverse selection and moral hazard could not be processed. Similar problems emerged on a less serious level at MFO3. Investment in an effective MIS is costly as "off-the-shelf" systems are often too rigid or do not suit a particular MFO. To strengthen organizational capacity, policy makers need to recognize the importance of an appropriate MIS. Rather than directly intervene in credit markets, they could help to build organizational capacity by channeling funds into staff training, software development, and business management.

Overcoming the problems of adverse selection and moral hazard in financial contracts can promote both outreach and financial viability. Lenders MFO1, MFO2 and MFO3 relied on screening and the use of collateral or collateral substitutes, while MFO4 used peer monitoring and joint liability to try and reduce information asymmetries and incentive problems. By not requiring any formal collateral, MFO1 considerably reduced this barrier to accessing finance for low-income individuals. However, its screening technology has not developed to sufficiently accurately evaluate the future income streams of small businesses enterprises (SMMEs), and hence, loans were limited to formally employed people. It will become more important for microlenders to expand their financial technologies to provide financial services to SMMEs as the formally employed target market becomes increasingly saturated with consumption loans. The screening technology used by MFO1 relied on both statistical scoring techniques and its branch managers' localized knowledge to reach relatively poor clients. The role of the loan officer's localized knowledge should, therefore, also not be underestimated. Micro-credit markets for SMMEs in SA have not yet developed to the stage where statistical screening mechanisms can be used.

Information about the stability of expected future income streams and expenditure patterns is not always readily available from SMMEs since the business and household income and expenditure are not always kept separate. Information obtained from the savings behaviour could be used by MFOs to learn more about the typical cash flow patterns of SMMEs. The flow of funds into and out of the savings account can be monitored to determine the stability of income streams. Savings can also be used as collateral against which funds can be leant as MFO2 has demonstrated. Where legislation allows microlenders to offer savings services this may encourage private institutions such as MFO1 to expand financial services to SMMEs. This may avoid some of the problems experienced by MFOs trying to mobilize savings with limited organizational capacity and experience.

Savings behaviour can be built into credit scoring models like those that have been effectively used by MFO1 to reduce information asymmetries. While statistical scoring models will not replace the knowledge base of loan officers in the microfinance sector, they are a useful tool that can enhance and speed up credit decisions. Where possible, MFOs need to develop such tools to improve the quality of the credit decisions. This is even more critical in SA where policy makers are concerned about the relatively high interest rates charged by microlenders. Cost reduction via reducing bad debts will thus become increasingly important in the SA microfinance sector. While credit scoring tools can reduce information asymmetries, they are data intensive and many MFOs may not have the necessary MIS to store the required data.

In the absence of formal collateral, MFO1 relied on effective monitoring and borrower reputational capital to create the necessary repayment incentive mechanisms. A well-developed MIS facilitated borrower monitoring, with credit controllers being notified within a day of an instalment being late and immediate telephonic follow-up being actioned. The monitoring technology relied heavily on telephonic contact, which limited MFO1's outreach to certain sectors of formally employed clients. This lending technology may be less suited when lending to SMMEs and small-scale farmers, although it could be implemented if individuals have access to cell phone technology.

The most important incentive mechanism for MFO1 was the threat of termination of the contract upon default. This rule is rigorously applied by MFO1 and can build reputational capital where information sharing between lenders is effective and where all lenders consistently apply this rule. The highly competitive market in which MFO1 operates has made the application of this rule more difficult since some lenders have less stringent debt forgiveness policies. The sequencing of loan terms and conditions is also more difficult in a competitive market since borrowers have access to alternative credit sources. In the SMME and emerging farmer sectors, reputational capital and the sequencing of loan terms and conditions may still have a powerful incentive effect since these markets are not subject to the same level of competition as the consumer loans market in SA. In the consumption loans sector, information sharing between lenders is likely to become more important. Credit bureaus have performed this task in SA, and it is important that this information is correct and fully reflects the credit behaviour of borrowers.

Policy makers need to ensure that lenders submit consistent and accurate information to credit bureaus while not compromising the integrity of this information and the incentives that it creates to encourage borrowers to align their behaviour with the lender's objectives. In addition, MFO staff that use this information must be trained to interpret it correctly given that different MFOs may have different aging processes and write-off rules. This is where lender organisations such as the Consumer Credit Association (CCA) to which MFO1 belongs provide lenders with guidelines on the different debt aging practices used by MFOs. The new proposals to improve the quality of the bureau data will help in this regard, while the NLR will also prove useful to microlending institutions if all lenders submit correct information. The consistent application of the rule of no further access to credit if a borrower defaults also needs to be applied rigorously by all lenders if reputational capital is to be effective. To maintain the integrity of reputational capital, MFOs must not compromise their credit granting rules in order to achieve sales targets as this could increase bad debts.

Lender MFO2 has relied increasingly on formal types of collateral to secure loans and a formal screening procedure to assess the risk of the loan applicant. This is lengthy, since detailed information on the loan applicant's business venture of the loan applicant is required. Formal collateral creates another entry barrier to financing for SMMEs and emerging farmers, allowing only those with relatively large businesses and accumulated wealth to apply for loans. This technology may not expand access to microfinance by SMMEs, as shown by MFO2's marked increase in average loan size. While the access to funds is not restricted through collateral by MFO3, the delegated monitoring by the sugar mill staff has caused problems in loan collection. Although, funds are deducted upon delivery of the sugarcane crop, borrowers can deliver on other individuals' grower codes or simply decide not to produce sugarcane.

This again illustrates the trade-off between intensive client monitoring and the absence of collateral. Monitoring is costly but essential where insufficient incentives are built into the contract to encourage the borrower to repay. MFO3 could consider improving its ability to monitor growers and to better incentivise the delegated agents doing its monitoring to be more effective. The SA sugar industry should also consider limiting the allocation of grower codes to households and not allocate grower codes to individuals. Group lending, although successfully used by MFOs such as the Grameen Bank and BancoSol, requires specific conditions to succeed. This technology may be less effective in providing access to credit for farmer groups in rural KZN that were large, with members that were spatially dispersed (individuals did not benefit from monitoring each other), not well constituted (limited investment in group formation), and heterogeneous. In addition, loan repayment was seasonal, and so frequent contact between staff and borrowers was not maintained to instill borrower discipline and group cohesion. Constituting and maintaining farmer groups may also impose high costs on both the borrowers and the lender (owing to substantial investments in group formation) and may, therefore, be a less desirable form of collateral for financing emerging farmer groups.

The group loan concept tended to be more applicable in urban areas of SA, where the groups were small (4 - 6 members), homogenous and members made regular monthly repayments, bringing them into contact with the lender who could then monitor group performance closely. However, high administration costs of group lending programmes negatively impact on financial self-sustainability.

Such costs may be reduced by introducing MISs at branch level, and achieving a scale of operations that spreads costs over more loans. A focus on sales rather than viability, the lack of discipline to follow-up on groups, and the scrapping of compulsory deposits negatively affected the functioning of groups financed by MFO4 and ultimately led to unacceptably high bad debts.

A compulsory savings account is necessary to limit the pressure on group solidarity. Where this is absent, group members may not want to continue to pay outstanding debts for defaulters. Again, loans have to be graduated to create the right incentives, while loan default must be penalized by immediate default. While these procedures were applied by MFO4 with varying degrees of success, a problem within the groups was that the performance of the businesses within the group was not uniform. This created tension as different members of the group had varying credit demands. Group lending can overcome information asymmetries, but its application is more complicated. The lesson is that thorough understanding of the target market is necessary before this technology can be applied.

The four financial technologies used by the study MFOs differed markedly in their ability to reduce information asymmetries. The need to develop suitable information processing capabilities and collateral substitutes is critical. Reputational capital was used with reasonable success and its broader application in financing SMMEs in SA is possible. The information processing capabilities of MFOs need to be adapted either by using local agents or having an MIS system that can accumulate information over time to improve decision making. Using formal collateral may be less desirable and may increase the barriers to finance for SMMEs. The process of "learning by doing" and careful experimentation should be encouraged when adapting MFO financial technologies to finance SMMEs and emerging farmers.

Policy makers may also consider reforming the process of borrowers applying to go under administration as this presents a serious threat to the credibility of loan contracts in the South African microfinance sector. A process of accrediting administrators may prevent unscrupulous individuals or organisations presenting themselves as administrators and abusing the process by encouraging borrowers to go under administration while charging a fee for the debt administration. The criteria for going under administration could also be made very stringent such that the process is not a likely option for the borrower. A complicated legal follow-up process also hampers the enforcement of debt contracts. The time period from initiating legal action to the borrower's appearance in court is often long and tedious. A simplification of the process that 'fast tracks' the borrower's appearance in court may improve debt contract enforcement as lenders are able to act quicker to obtain a judgment against a borrower which is listed on the credit bureau and adversely affects the borrower's ability to apply for credit in the future.

A potential new business opportunity for SA MFOs lies in developing suitable loan products for SMMEs that have a relatively quick turnover of stock. Here the study MFOs may want to explore loan products that leverage savings information and provide for weekly or bi-monthly loan repayments that meet the cash-flow needs of SMMEs. This requires that MFOs identify the sectors that can be profitably serviced. Hawkers and small spaza shops may not require loans and would prefer savings or transmission facilities, while medium-scale businesses such as taxi owners or small contractors may require longer-term loan products. Policy makers and microfinance practitioners need to establish what products low-income consumers want rather than following a "top-down" approach in product development. This is particularly the case for MFO2 that has shifted away from financing small agricultural loans that were relatively costly to administer. The lesson is that for SMMEs and the small farming sector, policy makers need to promote the income-generating capacity of these sectors rather than solving liquidity constraints with additional credit.

The importance of savings mobilization should not be underestimated. Savings can be a substitute for credit in liquidity management and provide collateral against which credit can be granted. In order to offer savings facilities and use savings behaviour as a source of information, financial institutions need to offer in-house savings facilities. This requires cash handling facilities, a MIS that can process savings, and the appropriate administrative capacity to deal with savings. Typical NGOs do not meet all of these requirements and, therefore, may not be in the best position to mobilize savings. Evidence from MFO2 suggests that rural, low-income individuals do save, but these savings have to accessible, while the MFO must be trusted by clients to take deposits. Established MFOs such as MFO1 and MFO2 have an advantage in developing this trust compared to the village banks that began operations by mobilizing savings.

Financial sustainability promotes permanence which also has important incentive effects, especially where reputational capital is being used as a collateral substitute. If MFOs are not perceived to be permanent, borrowers will have less incentive to repay the credit. Only MFO1 in the study was financially viable, while the other three MFOs were subsidy-dependent - this is not necessarily a problem if access to donor support is not threatened (as shown by MFO3). Sustainability, however, requires profits for reinvestment, which are generated by a suitable interest rate spread and control of administrative costs and arrears. Lender MFO1 charged high nominal interest rates while keeping arrears under control.

The question remains whether borrowers can afford to pay such high nominal interest rates in the long-term. Shareholder pressure has to some extent compelled MFO1 to charge high interest rates to maintain profit targets. Extending financial services to SMMEs and the emerging farm sector in SA will require lower interest rates than MFO1 currently charges. The question remains whether shareholders will allow this. The agricultural MFOs had relatively high arrears which, together with low interest rates, are not conducive to financial self-sustainability.

Operational efficiency and arrears control can be achieved by giving staff appropriate incentives for loan sales and loan collections. Branch efficiency can be improved with well-defined policies and procedures and a MIS to support these. Reaching economies of scale also promotes financial self-sustainability, but requires that the financial technology must be replicable and that there is a demand for the financial services. The MFO must also have access to capital that is necessary for the expansion process.

An important challenge for microlenders in SA is the control of costs as loan portfolio expansion slows down. Portfolio efficiency is a key indicator of cost efficiency and is a function of loan size and transactional efficiency. Consumption loans are prone to reduce transactional efficiency since borrowers need funds regularly while there are limits on the extent to which loan size per customer can increase without increasing the loan term. The challenge for MFOs will be to manage this by diversifying their portfolios across geographic regions and across different sectors in the economy (e.g. not just financing individuals that are employed, but also financing SMMEs). In a competitive market this will be more challenging and should increase the drive to develop suitable financial technologies for SMMEs and emerging farmers.

Results show that the credit granting decision for MFO1 staff was influenced by borrower credit-worthiness, ability to repay, contactability and income stability at all three branches (Ladysmith, Pretoria, and Pietermaritzburg). Credit bureau information was consistently a key source of information used by branch managers in deciding to grant credit. This highlights the need, firstly, for branch managers to be properly trained to interpret and use this information, and secondly, that the information supplied to the credit bureau be accurate. If the ability of credit bureaus to keep this information is constrained, it will hamper MFO's efforts to address the problems of adverse selection and moral hazard.

The focus should be on maintaining the quality of information supplied to the credit bureau. Heavy reliance on this information by MFO1 shows the role of reputational capital as collateral. Competitive pressures in the SA microfinance market may diminish the effect of this collateral type where borrowers use one credit source to repay the other. If this is not properly reflected in the borrower's payment profile information, it may lead to adverse selection problems.

Borrower affordability is also a key concern for MFO1 branch managers, as borrowers with debt-to-disposable income ratios over 25% were not granted credit. This is in line with the norms recommended by the MFRC. Such information is also obtained from the credit bureau, again highlighting the need for information-sharing between lenders. Such sharing between microlenders in SA is still problematic, but the NLR endeavours to overcome this problem. This must be done speedily if the level of indebtedness amongst clients is to be effectively controlled. Credit rationing by MFO1 staff was more severe where loan applicants were less contactable.

Loan applicants with less stable expected future income streams were less likely to be granted credit. This highlights the effect that exogenous shocks can have on the portfolio quality of MFO1. Changes in the economic environment can rapidly affect the profitability of economic sectors and job stability for borrowers. This implies that MFO1 staff must monitor its exposure to borrowers in different economic sectors, and that portfolio diversification, both geographic and across economic sectors, can reduce lending risks.

The stringent credit rationing criteria used by MFO1's managers prevented payment profile data supplied by the credit bureau from being used to assess loan default since most borrowers in arrears were not granted credit. For the Ladysmith branch, loan repayment was affected by borrower age, economic activity and borrower indebtedness. The impact of economic sector on loan repayment performance highlights the need for a well-diversified portfolio across economic sectors to reduce systemic credit risks. It also indicates that loan staff at MFO1 are very aware of this factor. Previous defaults and economic sector employed were directly linked to loan default for the Pretoria Branch.

Although most loan applicants with default information were credit-rationed, those that were granted credit still proved to be repayment risks. Branch managers could thus consider stricter rationing according to this variable. The role of default information also underlines the role of credit bureau information in predicting loan default. This information needs to be shared between lenders to improve the credibility of reputational capital as collateral. Credit bureaus need to be allowed to retain this information, as it is a key predictor of future loan repayment performance. Better borrower contactability reduced loan default, and branch managers at Pretoria should ensure that borrowers are contactable at home. Borrowers who had been employed longer at their current employer and who owned their home, were less likely to default (reflect expected income stability).

Higher previous bad debt, a higher debt-to-income ratio, economic sector employed in, and total number of recent inquiries positively affected loan default at the Pietermaritzburg branch. Higher indebtedness means that branch managers must accurately assess their clients' repayment capacity. Branch managers should also focus on achieving a good portfolio mix to reduce exposure to systemic credit risks. Model results testing the efficacy of the loan granting decision for MFO1 suggest that branch managers have adequately identified key factors that affect loan repayment. Loan applicant characteristics that lead to a greater likelihood of acceptance also decreased the probability of loan default. Borrower contactability, stability, debt commitments and previous credit history all influenced both loan granting and loan repayment decisions.

An effective loan screening mechanism is critical for MFO1, since it relies on a screening intensive loan technology to minimize the risk of loan default. The negative correlation between the error terms of the equations in the bivariate probit model suggest that the unexplained variances in the credit granting decision decrease the likelihood of loan default. Branch managers at MFO1 may thus be somewhat conservative in their credit granting decisions, particularly for first-time loan applicants. Given the trade-off between rationing credit and securing profits, these managers need to find the correct balance between perceived credit risk and expected profitability. Finally, the need to account for sample selection bias when estimating loan default equations is highlighted by different prediction probabilities in the unconditional and conditional probit models. Conditioning for sample selection bias is critical when developing credit scoring models that apply to "through the door" loan applicants. There is also a need for MFOs to store information on rejected loan applicants.

The estimated loan default model for MFO2 highlighted some key characteristics which could improve its screening procedures and help to develop a formal screening model for emerging farmers, SMMEs and agribusinesses. Economic activity of the borrowers is a key factor for loan officers to consider, as ploughing contractors and broiler producers tended to be in arrears and in default. Ploughing contractors probably needed closer monitoring to ensure that equipment is properly maintained and sufficient income can be obtained to repay loans. They could also be encouraged to diversify into contract transport (e.g. sugar-cane, timber or inputs) to improve liquidity. Given increased competition and the periodic outbreak of disease in the chicken industry, caution should be exercised when financing broiler production ventures in KZN. Borrowers need to be made aware of the management requirements and should be encouraged to diversify to reduce price risk.

Results also suggest that clients with larger loans are less likely to default. These loans tended to be associated with more (verifiable) collateral, lower administration costs per unit of credit and, probably, better quality information on potential investment returns. Larger borrowers also tended to produce for sale and had well-diversified asset bases that enabled them to better manage negative income shocks, and to avoid diverting funds for loan repayment to current consumption. Increasing the owner's equity stake in the business increases the share of the risk borne by the client and gives him/her more incentive to repay the loan. Although this measure is a second best option, it can be an alternative when collateral is ineffective in enforcing loan contracts.

Borrowers having an established record with the lender tended to repay their loans, highlighting the importance of reputation in a borrower-lender relationship. Borrower liquidity (expected total annual income relative to annual debt obligations) also helped to distinguish between high- and low-risk borrowers. This debt coverage measure focuses on *total* borrower income, rather than income generated only by the project, given that borrowers may divert funds for loan repayment to other uses such as funerals, weddings, food and clothing. Lenders, therefore, need to focus on total borrower liquidity and not only on the income generated by the intended investment, as an indicator of loan repayment capacity.

The results of the three analyses suggest that there is scope for lenders to adapt their financial technologies to improve the provision of rural financial services in KZN and other parts of SA. Agricultural lenders need to focus on improving service quality and loan contract enforcement. The microlenders face the challenges of broadening their financial product range to accommodate the needs of low-income individuals. The importance of mobilizing savings requires that the savings and credit functions be managed by the same financial institution. This will reduce borrower transaction costs in accessing financial services, promote financial self-sustainability, and encourage the use of savings as a source of collateral and information.

This study has highlighted three areas for future research. Firstly, there is a need to improve access to borrower information in order to make recommendations for improving financial services. It is very difficult to get access to information from MFOs, and this often requires considerable commitment from MFOs, which is not always forthcoming. Researchers also need to understand the business processes of the MFOs and the business rules that define how they handle data storage. This is not an easy process, particularly where the MFO derives no immediate direct benefit from the work being undertaken. Private consultants, large credit bureaus and credit risk management companies mostly undertake loan default studies.

Secondly, appropriate loan default models require very large sample sizes. Working with such large datasets requires good database management skills, especially where information from credit bureaus needs to be incorporated into the analyses. Future research should also focus on developing financial technologies that can improve access to financial services by SMMEs. Thirdly, more research is needed on the impact of interest rates on loan demand and the quality of loan applicants. High interest rates charged by microlenders are of concern to SA policy makers. If lower interest rates attract a better quality client in larger volumes, this will benefit microlenders.

SUMMARY

Growing concerns about poverty stem from the need to achieve growth with equity through policies that foster participation of the poor in the process of economic development. While the linkages between economic growth and poverty reduction are not perfect, it is difficult to imagine a significant decline in poverty in the absence of economic growth. Concerns about access to credit were prompted by the absence of formal institutions, such as commercial banks, in rural areas, assumptions that rural individuals were too poor to save, and to encourage productive investment and technology adoption. Results of these programmes were poor with lending institutions recording high default rates, having limited outreach and being largely subsidy dependent.

Economic growth in developing regions may be improved through fostering well functioning markets and improving institutions that facilitate the ownership and transfer of property rights with a legal environment that adequately enforces contract law. Financial institutions, formal and informal, represent part of the essential institutional infrastructure required for the efficient functioning of markets. The most important contribution of financial intermediation is its ability to induce larger size and foster a greater degree of integration of markets for goods and services, factors of production and other assets. This promotes the division of labour and increased specialisation, greater competition, use of modern technologies and exploitation of economies of scale and scope. This is achieved through the provision of monetization services, management of the payments system and intermediation between surplus (savers) and deficit units (investor/borrower) which facilitates channelling of resources from individuals, activities and regions with limited growth potential to those where more rapid expansion is possible. Financial intermediaries also facilitate risk

management and consumption smoothing over time by allowing synchronisation between income generating and consumption activities.

The indirect role of finance in economic development and the poor performance of directed credit programmes, led to the emergence of a new institutional view of micro finance. This 'new view' promoted the development of financially viable lending institutions that provide a wide range of demand driven financial services to a broad range of clients. High levels of outreach and self-sustainability, however, require innovative and cost effective financial technologies to overcome information asymmetries, the absence of formal collateral and the lack of complementary institutions prevalent in rural financial markets.

Most challenges in rural financial intermediation arise from the promissory and intertemporal nature of financial contracts. Asymmetric information between borrower and lender creates problems for lenders in distinguishing between high and low risk borrowers and deciding whether borrowers will adopt a riskier project during the term of the loan. Together with difficulty in contract enforcement, this has led to the poor frequently being rationed out of formal credit markets.

In addition, both borrowers and lenders incur transaction costs in accessing and providing financial services. For the borrowers, these include out-of-pocket costs to access financial services, legal fees and the opportunity costs of time. Lender transaction costs arise from gathering information, collecting and disbursing funds, administering financial services and loan contract enforcement. High transaction costs may also result in external credit rationing by lenders or internal rationing by borrowers.

Innovations in rural financial markets have focused on reducing transaction costs by improving financial technologies and overcoming information and loan contract enforcement constraints. 'Best practice' MFOs in Indonesia, Asia and Latin America have reduced borrower transaction costs via establishing extensive branch networks and mobile banking services which increase accessibility to clients. Customising loans and savings products accommodates needs and preferences of clients. Short-term loans with flexible loan sizes and repayment terms, have allowed a wider variety of activities to be financed while accounting for seasonality of cash flows.

Loans have simple application forms and fast approval times (one to two weeks) facilitated by decentralised decision making. Lenders have reduced transaction costs by using effective management information systems (MISs) that can instantly track loan status, reducing paper work, and motivating staff with financial and non-financial incentives linked to quantifiable performance based indicators such as number of clients, portfolio growth, branch profits *and* loan collections. In addition, branch structures have been kept lean while spreading costs over a large number of clients (achieving economies of scale).

Repeat loans to small borrower groups lower loan risk by providing initial small loans with frequent repayments to instil financial discipline and facilitate monitoring. Joint liability amongst borrowers is used as a collateral substitute with lenders requiring compulsory savings as a contingency fund to finance group members in arrears. Lenders with more flexible loan terms have used character references to screen and monitor borrowers, and interest rate rebates, reputational capital, loan guarantees and warehouse receipts as incentive and contract enforcement mechanisms. Borrowers have been held strictly accountable with no new loans granted without existing loans being repaid.

The charging of positive real interest rates that provide a suitable spread to cover operational costs and cost of funds, while protecting the MFO equity base, is also imperative for financial self-sustainability. Best practice institutions with innovative financial technologies and motivated management have achieved both scale (reaching large numbers of clients) and depth (reaching relatively poor clients) of outreach with high levels of financial self-sufficiency. Such MFOs have managed to perform in a variety of policy environments. However, low levels of inflation, suitable economic growth, stable political environments, and well established complementary institutions (credible legal systems, secure and transferable property rights, well established infrastructure) have contributed to self-sustainability and greater levels of outreach.

In South Africa, targeted credit programmes faced similar problems experienced in other developing countries. Given the lack of formal financial services in developing areas in South Africa, the government initiated targeted credit programmes to motivate productive investment and technology adoption. A multitude of MFOs were created to act as implementing agencies for the state. The institutions experienced high default rates with the credit not always reaching the targeted population. A new policy direction emerged which promoted more viable MFOs providing broad-based financial services including savings facilities to the rural poor.

The Strauss Commission was also established to develop a formal rural finance strategy for South Africa. While some proposals of the Strauss Commission were positive, the thrust of the proposals were in developing targeted, sector-specific credit programmes, which international experience has shown not to be viable. Private commercial lenders such as

ABSA Bank and NGOs such as the Financial Aid Fund of the South African Sugar Association and the Ithala Finance and Investment Corporation have shown considerable initiative in mobilising savings and providing credit to the rural poor using innovative financial products. In an effort to promote capital flows into developing areas the Government introduced an exemption to the Usury Act. The exemption resulted in the mushrooming of the micro lending sector that mainly focused on providing financial to low-income, formally employed individuals. Providing finance to SMMEs remained marginal. The challenge facing South African MFOs is to develop financial technologies that can expand the frontier of finance to this sector.

Previous rural finance research in South Africa has focused mainly on the role of credit in the production process, outreach and self-sustainability or on individual lenders. Given the new focus on evaluating credit providers and the lack of attention given to financial technologies, this study aims to assess financial technologies, outreach and financial viability of four institutions providing loans to households in developing areas of KZN. Understanding the limitations and advantages of current technologies and innovations, used by KZN lenders, may facilitate institutional reform to improve access of rural people to formal financial services. In addition data on borrower and loan characteristics were analysed using logistic regression to identify characteristics of clients who are current and in arrears both at a micro lending and agricultural MFO. The efficacy of the loan screening mechanism for one the study MFOs was also evaluated using a bivariate probit model conditioned for sample selection.

Data on financial delivery systems, contract enforcement and incentive mechanisms were obtained from four financial institutions in KZN. The four institutions differed in their objectives and target clientele. MFO2 and MFO3 focused on providing agricultural input loans to clients. These lenders were concerned mainly with promoting economic development and social upliftment of small farmers in rural areas and thus provided loan products to suit the needs of these development objectives. The loan products were mostly for income generating purposes. MFO2 had a range of short, medium and long-term loan products (including a short-term non-asset backed group loan for agricultural inputs) with no fixed limit on loan sizes. With increased focus on financial viability MFO2 changed is focus on financing larger commercially viable business ventures of emerging farmers and agribusiness. MFO2 stopped granting group credit to small, subsistence farmers as high default rates and administration costs reduced the viability of these loans.

MFO3 targeted specifically small farmers producing less than 450 tonnes of sucrose per year, and provided a long-term crop establishment and a short-term working capital loan. Loan terms were long which is characteristic of agricultural loans, while loan repayment schedules were flexible to accommodate the seasonality of agricultural production. Concessionary interest rates were charged on these loans although MFO2 changed this policy in-line with it drive to improve financial viability. In addition, compulsory own equity contributions were required by MFO2 to increase the incentives of the loan contract. More stringent collateral requirements and own equity contributions made it more difficult for low-income small-scale farmers to access finance from MFO2. MFO3 had relied on crop cessions as a contract enforcement mechanism.

While loan terms were flexible, the loan applications tended to be tedious for the agricultural lenders with loans being disbursed in-kind only. Long loan approval times, together with complex disbursal procedures increased borrower transaction costs. Loan disbursal and approval procedures were complicated for MFO3 because of reliance on the sugar mill administration process. This caused serious backlogs in loan application processing that resulted in loan approval times of up to 6 months. Streamlining this process will improve the quality of service that MFO3 can deliver to borrowers. MFO3 has already embarked on this process by employing its own staff at the sugar mills to facilitate the administrative procedure.

Micro-lenders extending credit for micro-business activities (MFO4) and consumption purposes (MFO1) had relatively smaller loans than the agricultural lenders with definite loan maxima imposed on loan sizes to comply with the Usury Act exemptions. These loans had more frequent and rigid repayment periods, partly to instil financial discipline amongst borrowers, while interest rates that reflect the true cost of lending were charged. MFO1 disbursed loans in cash with few restrictions on use, which represented an improvement in the quality of services to borrowers.

Loan applications procedures for the micro lenders varied. MFO1 had a well established and extensive branch network throughout South Africa, improving access to financial services. Loan approval times were relative quick (1 – 2 hours) with loans being disbursed in cash. The represented a substantial improvement in quality of service when compared to the agricultural lender although MFO2 and MFO3 required more detailed processed because the nature of the loan products. MFO1s greatest advantage was the strength of its administration system and cash handling facility at the branches. The good administrative system was facilitated by good governance principles and a MIS system that could track cash handling at branches.

The group formation processes at MFO4 did pose considerable transaction costs on borrowers although the absence of formal collateral requirements allowed low-income SMMEs to access the financial services. The absence of strong administrative processes and a well function MIS system at branches resulted in MFO4 having to rely on the transaction facilities of a commercial bank. Group leaders had to cash a cheque at the commercial bank to obtain the group's loan while payments also had be made at the bank and the deposit slip taken to MFO4. This process is likely to increase borrower transaction costs and detract from the quality of service. MFO4 also did not have a well established branch network. Hence it was costly and time consuming to get to the branches for borrowers.

In the case of group loans, MFO4 initially invested a considerable amount of time in group formation while MFO2 relied on the existing structures of local farmer associations. While this reduced administration costs of MFO2, in terms of extending a large number of small loans to small farmers, the group structures were weak, which consequently resulted in loan repayment problems. Group loans in themselves presented some inflexibility in terms of loan sizes and loan use between members. While they allow access of the rural poor with no suitable collateral to financial services, group loans become limiting where members require larger loans to grow their businesses. This was a particular problem for MFO4. With sales pressure mounting, investment in group formation was compromised. The result was higher bad debts that culminated in MFO4 having to be liquidated and restructured.

A particular problem also arose with borrowers having difficulty in interacting with the commercial bank. Processes were complicated while borrowers complained of poor customer service at the bank and the impatience of staff in assisting them with the banking process. These problems may make future interlinkages between commercial banks and less formal financial institutions difficult. Schoombe's (1999) approach of promoting interlinkages may thus be less practical in reality and policy makers should focus on encouraging existing micro lenders with a well developed infrastructure and technology to expand the scope of their financial services.

Having a suitable credit delivery system that provides quality financial services is important in terms of achieving good outreach. However, quality financial services need to be provided on a continuous basis, which requires the institutions not only to charge interest rates that reflect the true cost of lending, but to reduce loan default and achieve suitable loan collection rates. This requires lenders reduce information asymmetries, loan repayment incentive and contract enforcement problems. Few of the institutions had formal screening models, with only MFO1 employing a computerised system to improve both the speed and the accuracy of the loan approval process. However, the scoring models were used in conjunction with the localised knowledge of branch managers. Use of a scoring system was facilitated by a well functioning MIS system.

MFO4 used local group structures to screen individuals, which reduced both the geographic and ethnic distance between borrower and lender and thus improved the accuracy of the screening procedure. MFO3 made use of a loan approval committee with representatives from the local area. MFO2 had a formal applicant screening methodology where this screening methodology mainly focused on determining whether the investment project could carry the additional debt burden. Only MFO1s screening technology focused on determining whether borrower had the ability and willingness to repay.

Loan monitoring was difficult and costly for the agricultural lenders given the geographic dispersion of the clientele. The micro-lenders, given the use of financial technologies, which promoted frequent contact between borrower and lender, could monitor clients more regularly. In addition to initial borrower screening, lenders relied on collateral to enforce loan contracts and reduce moral hazard. Both collateral and collateral substitutes were used by lenders to enforce loan contracts. These included crop cessions, machinery and equipment, permission to occupy certificates, mortgage bonds on land, joint liability groups, third party guarantors and reputational capital. Crop cessions were less successful as collateral types because of defective loan collection mechanisms. Machinery and equipment was subject to high collateral specific risks due to poor maintenance and theft as well as high liquidation costs, which reduced the efficacy of this collateral.

Permission to occupy certificates had no value as collateral since they were not secure and tradable, giving them no market value. Mortgage land used by MFO2 had secure and tradable property rights, which gave it relatively high value as collateral. Joint liability mechanisms had mixed results with this collateral substitute being relatively more effective for small, homogeneous groups of micro-entrepreneurs having regular incomes to suit the frequent repayment patterns required by this method to instil financial discipline amongst borrowers and to promote frequent contact between borrower and lender.

Agricultural group loans consisted of large, heterogeneous groups with weak group cohesion due to the geographic dispersion. The seasonality of agricultural production did not suit the frequent loan repayment patterns while weak group cohesion and the limited contact between borrower and lender made this collateral type less applicable for agricultural loans. Reputational capital was used most successfully by MFO1 and MFO4. Given that MFO1 required no formal collateral types, the threat of termination of the borrower lender relationship was used to create the necessary incentive for borrowers not to voluntarily default. Listing defaulting borrowers with the credit bureau reinforced the mechanism. The mechanism of slowly improving the loan terms and conditions for borrowers who repay their loans on time was absent. To some extent this was prompted by the highly competitive nature of the market where severely credit rationed borrowers could easily source alternative credit.

The reputational capital to work effectively it is critical that new loans are not granted to defaulting borrowers. Where this happens, the power of the incentive mechanism is weakened. This is true to some extent for the South African micro lending market where the level of competition is high but information sharing is imperfect, because not all lenders submit information to the same credit bureau. The National Loans Register administered by the MFRC is trying to overcome this problem but it will take time before the level of information sharing is improved amongst the micro lenders. The joint liability groups of MFO4 worked less well as incentive mechanism. This was mainly as a result of the group formation processes being relaxed and abandoning the compulsory savings account because borrowers felt uncomfortable in transacting with the commercial bank.

Costly and ineffective legal procedures also contributed to the loan repayment problem. It is important that borrowers are sanctioned for default to reduce the possibility of voluntary default. This can be achieved by providing sufficient penalties that are enforceable by law. This may also reduce the culture of non-payment, which exists amongst borrowers. Limited savings mobilisation was undertaken by the MFOs, except for MFO2, which had an extensive savings mobilisation network. Savings have a far greater potential of reaching rural poor as shown by the large number of savers relative to borrowers for MFO2. In addition to savings providing an important substitute for credit, they can provide an important source collateral and information on potential borrowers. Savings can also assist lenders in reducing dependence on donor funds. It is, therefore, important that savings and loans be provided together. This will also help in reducing transaction costs of borrowers in having to access financial services at different financial institutions.

However, to offer saving facilities requires organisation competence, sound administration, cash handling facilities, and a good MIS that can accommodate savings. MFO1 has all these qualities and is in the position to expand the scope of its financial services. Offering savings facilities will also help MFO1 acquire more knowledge about potential customers, particularly SMMEs. Savings may thus enable MFO1 to broaden its financial technologies to provide finance successfully to SMMEs. This will present an important expansion in the frontier of micro finance in South Africa.

Self-sustainability indicators showed that the development orientated lenders were subsidy-dependent although MFO2 is working towards achieving a greater level of subsidy independence. MFO3 will continue to remain subsidy dependent as its focus is development finance. However, subsidy dependence has not detracted from MFO3's focus of achieving cost efficiencies through utilising the infrastructure of the sugar mills. This has, however, impacted on its ability to deliver quality financial services. The continued reliance on donor funds may also constrain MFO3 from being able to improve the quality of service without incurring additional costs.

MFO1 was highly profitable as a result of achieving economies of scale while managing to contain bad debt levels. Charging relatively high interest rates has also contributed to MFO1's profitability. The ability of MFO1 to continue to charge these high interest rates may be constrained as the micro credit market matures and as borrowers become more aware of the cost of credit. Hence MFO1 will have to focus on improving its cost efficiencies to maintain its profitability levels.

Outreach of loans for MFO2 poor and is a reflection of the limited accessibility of the loan products while they were also aimed at larger, more wealthy rural borrowers. Low average number of loans outstanding and high volume of loans disbursed for MFO2 substantiates this. Accessibility of financial products has been improved with the restructuring of MFO2 such that all agricultural loan products are available throughout its extensive branch network and not only at selected branches. Arrears for the development lenders were relatively high, which is a reflection of the poor loan collections achieved. This has resulted from difficulties with collateral types while droughts and payment boycotts have also contributed to this. Poor loan collection promotes continued subsidy dependence and should be kept to a minimum.

Accurate arrears and cost information was not available for MFO4. However, interviews with staff suggested that MFO4 had incurred high arrear rates because of poor administration and control of borrower groups. MFO1 and MFO3 have been able to achieve a considerable depth of and breadth of outreach while MFO2 has shifted its focus to less expensive large loans. MFO4s outreach was relative limited. There are several reasons for this with the most important being the inability to achieve economies of scale, possibly due to the lack of funding. Its administrative capacity was also limited. In addition, it is not clear whether there is a massive demand of financial services by SMMEs. The performance of SMMEs is linked to a well functioning and growing economy. Small business may more constrained by high transaction costs of doing business and access to markets rather than being liquidity constrained.

Effective borrower screening does not only increase the ability of lenders to reduce the problem of adverse selection but may also speed up loan approval times. Data on both accepted and reject clients was collected from MFO1 with the objective of firstly determining the factors that influence the credit rationing decision. Loan performance information was also observed for those loan applicants who were granted credit to determine factors that influence loan default. Finally, the efficacy of the credit granting system was evaluated using a bivariate probit model conditioning for sample selection bias.

Key factors that emerged as important credit rationing criteria were loan applicant income stability, contactability, ability to repay the debt and loan applicant credit history as provided by the credit bureau. Importantly these results did not vary across the three study branches. Loan officers were very aware of the economic sectors in which borrowers were employed as the risk of retrenchment or short jeopardised the stability of the future income streams. Although the nature of the employment sectors varied from branch to branch, borrowers who were regarded as being employed in stable economic sectors were less likely to be rationed. Contactability by telephone was a very important component of MFO1s monitoring technology. Hence the importance of this variable in the screening decision. Loan applicants where were less contactable by telephone either at work or at home were more likely to be credit rationed.

The reliance on telephonic contact also highlights the inability of this type of technology to deal with SMMEs. Monitoring masses of borrowers is not possible for MFO1 because it would too costly. Telephonic contact is thus a substitute, albeit imperfect, monitoring mechanism. Also important is that the bigger the company and the higher the bad debt the greater the monitoring cost is. It is also a cost that is difficult to control since the telephone network is owned by a state monopoly in South Africa.

Loan applicants who had existing debt commitments that exceeded 25% of their net 'take-home-pay' were also more likely to be rationed. Ability to pay is a critical component of MFO1s rationing decision and is evaluated using the payslip information present on application. Inherent in this is also a potential shortcoming of MFO1s financial technology since the ability to assess affordability of business incomes is not possible. The most important rationing criteria for MFO1 was the previous credit history information provided by the credit bureau.

This highlights some important characteristics of MFO1a credit technology. Firstly, it does rely on the reputational capital of borrowers. Borrowers with worse credit histories as manifested by payment profile arrears, defaults and judgements were not likely to be granted credit. Secondly, it highlights the importance of accurate credit bureau information since a large part of the rationing decision is based on this data. Improvements in the quality of information may enhance the decision making capabilities based on bureau data. It is also important that branch managers know how to interpret the data based as arrears reporting by lenders vary.

Factors influencing loan repayment performance varied between the branches. However, common factors that affect loan repayment performance were borrower ability to repay, previous defaults, contactability and economic activity. In addition, older borrowers were less likely to default at the Ladysmith branch while borrowers who had been employed for a longer at the current employer were less likely to default at the Pretoria branch. Borrowers that were more contactable were less likely to default. This highlights the importance of loan monitoring in a technology that is less collateral intensive. However, monitoring is costly and needs and needs to be balanced against the returns achieved with that additional monitoring. The importance of employment sector in the affecting the likelihood of repaying the loan highlights the impact that economic shocks can have on MFO1. Secure employment is a pre-requisite for a guaranteed future payment stream important to repay the loan.

However, economic instability that results in retrenchments or staff being put on short-time may have adverse effects on borrowers ability to repay and thus expose MFO1 to considerable systemic risk. It is, therefore, important that MFO1 ensures a reasonable level of diversification of its loan portfolio across employment sectors at a branch level to eliminate the adverse impacts of exogenous economic shocks. Branch staff are acutely aware of this given that employment sector variable was also important in the credit rationing decision.

Ability of borrowers to repay the loan is also an important determinant of loan repayment. On average, borrowers who had more that 18% of their monthly, disposable income committed to repay debt with other lenders were less likely to repay the loan at MFO1. Low-income borrowers have relatively lower levels of liquidity and are thus less able to carry high debt loadings. This confirms the concerns raised in the study of borrower indebtedness commissioned by the MFRC. It is thus important that MFO1 staff take cognisance of the existing debt commitments of loan applicants and possible ration loan applicants with higher debt commitments more. It is also important that MFOs are made aware of the borrowers' existing debt commitments. This is something that the NLR aims to achieve. Greater awareness of borrower debt commitments will result in better loan granting decisions. This does, however, depend on how consistent the rule is applied across lenders.

The importance of previous credit history in loan repayment performance emphasised the value of this information in the loan granting decision. Borrowers with a higher number of previous defaults were more likely to default again. By not granting loans to borrowers that have previously defaulted, MFO1 can enhance the value of reputational capital. It is also important that this rule is applied consistently across the lending industry. The value of this information also highlights the importance that bureaus keep this information and make it available to the credit industry.

The efficacy of the credit granting decision was evaluated using a bivariate probit model that conditions for sample selection bias as repayment performance is only observed for those borrowers that are granted credit. A positive (negative) and significant coefficient in the loan granting equation, together with a negative (positive) and significant coefficient in the loan repayment equation would suggest that MFO1 is using the information correctly to grant or deny credit to loan applicants. The results of the bivariate probit model suggest that MFO1's screening mechanism is effective in correctly identifying high and low risk borrowers. Loan applicant contactability and stability have a positive and significant coefficient in the credit granting equation and a negative and significant coefficient in the loan repayment equation.

The debt-income ratio, number of bad debt write-offs and payment profile arrears have negative and significant coefficients on the loan granting equation and positive and significant coefficients in the loan repayment equation. Only payment profile information has a non-significant coefficient in the loan repayment equation. This is because most of the loan applicants who had payment profile arrears were fully rationed. The negative correlation coefficient between the credit granting and loan repayment equations is negative, suggesting that loan officers were somewhat conservative in their credit granting decisions. This is not necessarily bad but there is a trade-off between risk and profits. The optimal point at which to ration credit needs to be determined by MFO1. Evaluating the efficacy of the screening mechanism is important for lenders since poor screening results in higher bad debts.

Data were collected on individual borrower characteristics of medium-term agricultural loans extended during 1993 and 1994 by an MFO2. A total of 59 observations were obtained. Initial descriptive statistics show the majority of borrowers to be men with only 17 per cent being women. Men, on average, received relatively larger loans than women, with companies and partnerships receiving the largest loans. The activities financed were mainly livestock production, timber and sugarcane contracting, maize milling and contract ploughing and cartage. Livestock production loans included loans for the purchase of broiler equipment, feed and day-old chickens. Loans for timber and sugarcane contracting ventures involved the purchase of equipment while loans for maize milling were used to buy hammer mills. Loans for contract ploughing and cartage involved the purchase of tractors, trailers and ploughs.

Most of the male borrowers invested in contract ploughing and cartage ventures with most of the women being involved in broiler production. The largest number and volume of loans were disbursed by the Port Shepstone branch with loans for contract ploughing and cartage accounting for 78 per cent of the total value of loans disbursed. The Pietermaritzburg branch tended to also focus on broiler production loans.

Of the total of 59 loans disbursed, 17 were current, 10 were in arrears and 32 were in default. Both binomial and multinomial logit models were estimated to determine characteristics of borrowers that paid loans in arrears and in default. For the binomial logit model the 'arrears' and 'current' categories were combined to form a less stringent 'current' category. Borrowers who had larger loans, higher own equity contributions, had maize milling and timber and sugarcane contracting businesses and were relatively liquid were less likely to default on loan repayments. Larger loans tended to be associated with more verifiable collateral, lower administration costs per unit of credit and probably better quality information on potential investment returns.

A higher owner's equity stake in the business increases the share of risk borne by the borrower and provides more incentive to repay the loan. Ploughing and broiler contractors need closer monitoring to ensure that equipment is properly maintained and that sufficient income can be obtained for loan repayment. Contractors should be encouraged to diversify to improve liquidity. Given the increased competition and periodic outbreak of disease in the chicken industry, caution should be exercised when financing broiler production ventures.

The results for the multinomial logit model indicated that borrowers with larger loans and who had contract ploughing and broiler production ventures are more likely to pay in arrears. A few large loans were extended to borrowers entering into timber and sugarcane contracting as well as broiler production. Given the drop in price of chicken meat due to imports in 1994 the broiler producers could have experienced temporary repayment problems. Borrowers with smaller loans, lower own equity contributions, who entered into contract ploughing and broiler production ventures and who did not have a previous loan history were more likely to default. Borrowers having an established record with the bank tend to repay their loans, highlighting the importance of reputation in a borrower lender relationship.

Improved service quality together with more effective loan contract enforcement mechanisms are important areas of improvement for local MFOs and need to be considered by both policy makers and lenders when designing future rural finance policies. The loan default models also highlight key variables which lenders should consider for future borrower screening to promote viability and continued outreach.

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Appendix A

Loan and Financial Performance Evaluation Form for MFOs

Note : *This form should be completed by the head office of the Savings and Loans Division. This questionnaire is based on survey instruments developed by the Rural Finance Program at the Ohio State University, Columbus, United States of America.*

Note : ***All information will be kept strictly confidential and will only be used to compute outreach and financial performance indicators. The base information in this questionnaire will, under no circumstances, be published.***

Note : *All financial information should pertain only to those operations directly concerned with financial intermediation. For example, if a Micro Finance Organisation (MFO) lends and owns industrial hives, the entries provided here should be derived from accounts that pertain only to lending and deposit mobilisation operations and not to the industrial hives. The same convention should be followed if a MFO provides training and/or counseling services, in addition to, financial intermediation. The non-financial intermediation activities should be separated from the accounts.*

Note : *Many of the ratios require the calculation of annual averages. For example, return on assets is calculated as net income divided by average annual assets. Thus successive years of data are needed, at least for the stock figures. Unless otherwise stated assume that all information is required as at the beginning and end of the 1996/1997, 1997/1998, 1998/1999 and 1999/2000 financial reporting periods. The financial reporting periods should coincide with the financial year of the Savings and Loans Division. Income and Expenditure items required are those incurred during the indicated financial periods. Certain loan and savings data will be for disbursements and withdrawals during the financial periods. This will be clearly stated.*

Note : *Please enter N/A for "Not Available" for any requested data which the Savings and Loans Division is unable to provide.*

Note : *The reader is requested to read each question carefully.*

Note : *Should the reader have any query, please contact Manfred Kuhn. The telephone numbers are listed on the cover page.*

1. Dates of BEGINNING and END of FINANCIAL reporting period

	1996/1997	1997/1998	1998/1999	1999/2000
Date of beginning of financial period				
Date of end of financial period				

2. Balance Sheet Information

Please note that the balance sheets of the Savings and Loans Division may not be compiled in the same manner as described in this questionnaire. Please complete the information required here as accurately as possible and clearly describe any differences.

2.1 Assets

	1996/1997	1997/1998	1998/1999	1999/2000
Fixed Assets at Cost at beginning of period				
Fixed Assets at Cost at end of period				

Fixed assets should include all assets employed in financial intermediation, even if those assets were not paid for, but rather received as in-kind grants. For example, donated computer equipment may be a resource used by the Savings and Loans Division's operations and should be accounted for as such and depreciated over its useful life.

	1996/1997	1997/1998	1998/1999	1999/2000
Accumulated Depreciation at beginning of period				
Accumulated Depreciation at end of period				

	1996/1997	1997/1998	1998/1999	1999/2000
Loan portfolio principal outstanding at beginning of period				
Loan portfolio principal outstanding at end of period				

This is the amount of principal that has been lent out and has yet to be repaid. It should not include any accrued interest.

	1996/1997	1997/1998	1998/1999	1999/2000
Provision for Bad Debts at beginning of period				
Provision for Bad Debts at end of period				

This is a contra asset account. Any balance in it is subtracted from the balance in the account for Loan Portfolio Principal Outstanding. Here, the Performing Loan Portfolio is equal to the Loan Portfolio Principal Outstanding (an asset account) less any balance in the Provision for Bad Debts account (a contra-asset account). Any Bad-debt Provision expense increases the balance in the Provision for Bad Debts contra-asset account. When a loan is written off, the balance in the Provision For Bad Debts Account decreases. The idea is that some of the loans currently being made and some of the debts currently outstanding will end up being irrecoverable. To accurately reflect current performance, the expense caused by the writing off of these bad debts should be incurred in the period in which the loans are disbursed, not when the loans are eventually recognised as non-performing. Therefore, expenses for Bad debt Provision should be recorded more or less continuously as loans are made, but actual write-offs (decreases in the Provision for Bad Debt contra-asset account) are made only when specific loans are recognised as irrecoverable.

	1996/1997	1997/1998	1998/1999	1999/2000
Other Assets at beginning of period				
Other Assets at end of period				

Include all other assets not recorded in the previous asset items.

	1996/1997	1997/1998	1998/1999	1999/2000
Total Assets at beginning of period				
Total Assets at end of period				

The total asset figure derived from summing all the asset accounts in this questionnaire should equal the total assets that appear in the audited financial statements unless some non-financial operations had to be separated out.

2.2 Liabilities

	1996/1997	1997/1998	1998/1999	1999/2000
Deposits from Clients at beginning of period				
Deposits from Clients at end of period				

	1996/1997	1997/1998	1998/1999	1999/2000
Borrowings from Banks or other commercial sources at beginning of period				
Borrowings from Banks or other commercial sources at end of period				

This should include any funds borrowed from commercial sources, that is, sources that do not charge a "special", "preferential" or lower than market interest rate.

	1996/1997	1997/1998	1998/1999	1999/2000
Borrowings from Donors at beginning of period				
Borrowings from Donors at end of period				

This should include any funds borrowed from sources which: (a) charge a lower-than-market interest rate, or (b) are not in the business of making a profit or which are not owned by individuals seeking to maximise their own welfare. For example, the World Bank is not owned by profit maximising individuals. If the funds from a donor are lent at market rates, then classifying the funds as from a donor will not affect the subsidy dependence.

	1996/1997	1997/1998	1998/1999	1999/2000
Borrowings from Government at beginning of period				
Borrowings from Government at end of period				

This should include any funds borrowed from government at lower than market interest rates. E.g. Khula Enterprises, the National Housing Fund, the Development Bank of Southern Africa, the Land and Agricultural Bank or any government agency.

	1996/1997	1997/1998	1998/1999	1999/2000
Other liabilities at beginning of period				
Other liabilities at end of period				

This should include all liabilities that were not recorded in the above accounts.

	1996/1997	1997/1998	1998/1999	1999/2000
Total Liabilities at beginning of period				
Total Liabilities at end of period				

The total liabilities figure derived from summing all liability accounts in this questionnaire should equal the total liabilities that appear in the audited financial statements unless some non-financial operations had to be separated out.

3 Equity

	1996/1997	1997/1998	1998/1999	1999/2000
Total Equity at beginning of period				
Total Equity at end of period				

This is defined as the difference between Total Assets and Total Liabilities. ***Please also refer to section 5, which deals with the computation of Retained Earnings.***

4. Income Statement (or Statement of Profit or Loss) *(record revenues and expenses incurred during the financial period)*

4.1 Revenues

	1996/1997	1997/1998	1998/1999	1999/2000
Interest revenue from loans received in cash				
Interest revenue from loans due but not yet received				
Fee revenue from loans received as cash				
Fee revenue from loans due but not yet received				

	1996/1997	1997/1998	1998/1999	1999/2000
Other interest revenue				

This includes interest revenue derived from deposits in banks or from other investments.

	1996/1997	1997/1998	1998/1999	1999/2000
Grants in cash				

Grants are extraordinary revenue because they do not reflect the operations of the intermediary in the period. Grants must be included as revenue because the net worth of an entity increases when it receives a grant.

	1996/1997	1997/1998	1998/1999	1999/2000
Grants in-kind consumed				

Some grants are in-kind, and some in-kind grants are immediately consumed by the entity. Examples include advisors whose salaries are not covered by the Savings and Loans Division itself, or, travel and training provided at donor expense. These grants do not increase the resources *controlled by the Savings and Loans Division and thus do not increase assets, but neither do they increase the obligations of the entity and thus do not increase liabilities. In short, an expense is incurred, but no decrease to Net Income is experienced. Thus offsetting entries are made for the value of the grant in-kind that was consumed. One entry on the revenue side and one entry on the expense side. Thus all expenses incurred by the entity in its operations are recorded for use in productivity and efficiency measures, but the grants do not affect net income and thus do not affect net worth.*

	1996/1997	1997/1998	1998/1999	1999/2000
Grants in-kind that are not consumed				

Some in-kind grants are not immediately consumed. Examples include computer equipment or vehicles. These grants increase the Savings and Loans Division's assets because they increase the resources in the control of the Savings and Loans Division. For example, an in-kind grant of a truck with a cost of R10 000 would increase the fixed asset account on the balance sheet by R10 000. Depreciation would be expensed as usual over the asset's life. Such unconsumed in-kind grants are recorded as extraordinary income but not as an expense. This increases the net income and thus the net worth of the entity just enough to balance the increase in assets.

	1996/1997	1997/1998	1998/1999	1999/2000
Extraordinary revenue				

This includes revenue that is not the result of normal operations, such as gains on the sale of fixed assets.

	1996/1997	1997/1998	1998/1999	1999/2000
Other revenue				

Includes all other revenue not incorporated in the above items

	1996/1997	1997/1998	1998/1999	1999/2000
Total Revenue				

Total revenue as computed here will differ from the audited financial statements by the amount of accrued interest revenue and by the amount of in-kind grants (both consumed and not consumed, as noted).

4.2 Expenses

	1996/1997	1997/1998	1998/1999	1999/2000
Staff expenses				

This should include salaries, fringe benefits and bonus expenses of all staff.

	1996/1997	1997/1998	1998/1999	1999/2000
Materials and Equipment				

This includes payment for items such as paper, pens, consumables, telephones, cell phones, tea, and other assets which are consumed too quickly to be considered fixed assets.

	1996/1997	1997/1998	1998/1999	1999/2000
Other administrative expenses				

Any other administration expenses not covered in materials and equipment.

	1996/1997	1997/1998	1998/1999	1999/2000
Bad debt provision expense				

This is the amount that is added to the Provision for Bad Debt contra-asset account in the balance sheet in anticipation of irrecoverable debt. Ordinary write-offs of bad debt are subsequently charged to the Provision for Bad Debt contra-asset account. The level of provisioning should reflect the anticipated level of risk of bad debt in the current portfolio. It differs from the expense for extraordinary charge-offs in that provisioning expenses are part of the normal operations of a lender. All lenders have some bad debts as part of normal operations.

	1996/1997	1997/1998	1998/1999	1999/2000
Depreciation expense				

	1996/1997	1997/1998	1998/1999	1999/2000
Other operating costs				

Any other operating cost not covered in the above items.

	1996/1997	1997/1998	1998/1999	1999/2000
Extra-ordinary charge-offs				

This does not represent any ordinary loan-loss provision expense. It may be used, for example, when bad debts which have been accumulating for years without ever being written off, are to be written off.

	1996/1997	1997/1998	1998/1999	1999/2000
Grants in-kind consumed				

This should exactly equal Grants-in-kind consumed noted on the revenue side.

	1996/1997	1997/1998	1998/1999	1999/2000
Extraordinary expense				

This includes any expenses that are not part of normal operations and that are not included in other expense accounts. An example would be losses on the sales of fixed assets.

	1996/1997	1997/1998	1998/1999	1999/2000
Interest expense on borrowings from banks				
Interest expense on borrowings from donors				
Interest expense on borrowings from government				
Interest expense on borrowings from clients				

	1996/1997	1997/1998	1998/1999	1999/2000
Total expenses				

Total expenses computed above will differ from total expenses in the audited financial statements by the amount of in-kind grants consumed. Net income will differ only by the amount of accrued interest and in-kind grants.

5. Statement of Retained Earnings

	1996/1997	1997/1998	1998/1999	1999/2000
Net income				

This account may also be known as "operating surplus". This should be equal total revenue less total expenses as shown above.

	1996/1997	1997/1998	1998/1999	1999/2000
Dividends paid out				

This is amount of dividends paid to share holders.

	1996/1997	1997/1998	1998/1999	1999/2000
Accumulated profit at the beginning of the period				

This is the sum of capitalised net income from all previous periods.

	1996/1997	1997/1998	1998/1999	1999/2000
Paid-in capital at the beginning of the period				

This is the sum of all amounts received from all shareholders that have ever bought shares in the entity from the entity.

	1996/1997	1997/1998	1998/1999	1999/2000
Capital account at the beginning of period				

This should be equal to the sum of accumulated profit at the beginning of the period + paid-in capital at the beginning of the period. Even if the accumulated profit at the beginning of the period and paid-in capital are not readily available, the capital account at the beginning of the period should be known.

	1996/1997	1997/1998	1998/1999	1999/2000
Capital paid-in during the period				

This represents the amount received from shareholders buying newly issued shares directly from the entity.

	1996/1997	1997/1998	1998/1999	1999/2000
Capital account at the end of the period				

This should equal the amount of equity shown on the balance sheet for the end of the period.

6. Individual Loan Data

	1996/1997	1997/1998	1998/1999	1999/2000
Number of loans outstanding at beginning of period				

	1996/1997	1997/1998	1998/1999	1999/2000
Number of loans outstanding at end of period				
Amount of principal outstanding at beginning of period				
Amount of principal outstanding at end of period				
Provision for Bad Debt at beginning of period				
Provision for Bad Debt at end of period				
Number of loans disbursed in the period				
Amount of principal disbursed in the period				
Number of loans disbursed to first time borrowers in the period				

7. Group Loan Data

	1996/1997	1997/1998	1998/1999	1999/2000
Number of group loans outstanding at beginning of period				
Number of group loans outstanding at end of period				
Number of loans disbursed to groups in the period				
Number of loans disbursed to first time groups in the period				

8. Deposit Account Data

	1996/1997	1997/1998	1998/1999	1999/2000
Number of deposit accounts active at beginning of the period				
Number of deposit accounts active at end of the period				
Number of deposit accounts opened during the period				
Amount of deposit balances at beginning of the period				
Amount of deposit balances at end of period				
Amount deposited in the period				
Amount withdrawn in the period				
Number of deposit transactions in the period				
Number of Demand deposits at beginning of the period				
Number of Demand deposits at end of the period				

	1996/1997	1997/1998	1998/1999	1999/2000
Number of Demand deposits opened during period				
Amount of Demand deposit balances at beginning of the period				
Amount of Demand deposit balances at end of period				
Amount deposited in Demand deposits in the period				
Amount withdrawn from Demand deposits in the period				
Number of Time deposits at beginning of the period				
Number of Time deposits at end of the period				
Number of Time deposits opened in the period				
Amount of Time deposit balances at beginning of the period				
Amount of Time deposit balances at end of the period				
Amount deposited in Time deposits in the period				
Amount withdrawn from Time deposits in the period				

9. Loan Recovery Rate Information

The loan collection rate can be defined in a number of ways. The data requirements for each type of collection rate will be listed below. Please fill in the information for the method used by the Savings and Loans Division. If this data is available monthly then complete the information on a monthly basis with month1 and month 12 coinciding with the beginning and end of the financial year. ***(Please note: AMOUNT DUE and AMOUNT RECEIVED INCLUDE PRINCIPAL AND INTEREST)***

	1996/1997	1997/1998	1998/1999	1999/2000
Total amounts falling due for the first time during the period (this excludes overdue payments)				
Of the loan amounts falling due for the first time during the period, how much has been paid on time (excludes pre-payments)				
Total loan amounts due during the period (including overdue payments)				
Total loan amounts received during the period (including current payments, overdue payments and pre-payments)				

	1996/1997	1997/1998	1998/1999	1999/2000
All amounts due at the end of the period since the inception of the program (cumulative amounts due)				
All payments received at the end of the period since the inception of the program (cumulative amounts received)				

If the recovery rates are recorded on a monthly basis then the following tables should be completed.

Total amounts falling due for the first time during the period (this excludes overdue payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				
Month 4				
Month 5				
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

Of the loan amounts falling due for the first time during the period, how much has been paid on time (excludes pre-payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				
Month 4				
Month 5				

Of the loan amounts falling due for the first time during the period, how much has been paid on time (excludes pre-payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

Total loan amounts due during the period (including overdue payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				
Month 4				
Month 5				
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

Total loan amounts received during the period (including current payments, overdue payments and pre-payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				
Month 4				

Total loan amounts received during the period (including current payments, overdue payments and pre-payments)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 5				
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

All amounts due at the end of the month since the inception of the program (cumulative amounts due)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				
Month 4				
Month 5				
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

All payments received at the end of the month since the inception of the program (cumulative amounts received)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 1				
Month 2				
Month 3				

All payments received at the end of the month since the inception of the program (cumulative amounts received)				
	1996/1997	1997/1998	1998/1999	1999/2000
Month 4				
Month 5				
Month 6				
Month 7				
Month 8				
Month 9				
Month 10				
Month 11				
Month 12				

10. Loan Arrears Rate Information

The computation of an arrears rate depends on how the Savings and Loans Division defines the arrears rate. A standard definition of arrears will be provided below. If the Savings and Loans Division computes arrears differently, please provide an accurate definition in the space provided. Following the definition, please fill in the relevant amounts in the spaces provided.

	1996/1997	1997/1998	1998/1999	1999/2000
Amount of principal and interest overdue by 1 – 30 days				
Amount of principal and interest overdue by 31 – 60 days				
Amount of principal and interest overdue by 61 – 90 days				
Amount of principal and interest overdue by 90+ days				

These figures indicate the amount of payments that the Savings and Loans Division should have received as of the date of the balance sheet but had not, relative to the total loan portfolio outstanding. *Thus, if the loan portfolio consisted of one loan for R1000 and that loan had one payment of R10 overdue as of the date of the balance sheet, the arrears would be 10/1000 = 1%. If the organuisation does not age arrears, please not that and provide the unaged figure.*

	1996/1997	1997/1998	1998/1999	1999/2000
Total outstanding balance for loans with payments 1 – 30 days late				
Total outstanding balance for loans with payments 31 – 60 days late				
Total outstanding balance for loans with payments 61 – 90 days late				
Total outstanding balance for loans with payments 90+ days late				

These figures indicate the amount of the portfolio signaled to be at risk of becoming bad debt because one or more of the payments are overdue. *For example, if one R10 payment on a R1000 loan is overdue, the entire R1000 is at risk and the entire R1000 should be included in the arrears figure presented here. If the Savings and Loans Division does not age arrears, please note that and provide the unaged figure.*

If the above categorisation of arrears is different to that of the Savings and Loans Division, please indicate how the Savings and Loans Division defines arrears and then supply the relevant data in the spaces provided below.

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	1996/1997	1997/1998	1998/1999	1999/2000
Amount of principal and interest overdue …….. days				
Amount of principal and interest overdue by …….. days				
Amount of principal and interest overdue by …… days				
Amount of principal and interest overdue by …… days				

These figures indicate the amount of payments that the Savings and Loans Division should have received as of the date of the balance sheet but had not, relative to the total loan portfolio outstanding. *Thus, if the loan portfolio consisted of one loan for R1000 and that loan had one* *payment of R10 overdue as of the date of the balance sheet, the arrears would be 10/1000 = 1%. If the organuisation does not age arrears, please not that and provide the unaged figure.*

	1996/1997	1997/1998	1998/1999	1999/2000
Total outstanding balance for loans with payments ...... days late				
Total outstanding balance for loans with payments .... days late				
Total outstanding balance for loans with payments .... days late				
Total outstanding balance for loans with payments ......days late				

These figures indicate the amount of the portfolio signaled to be at risk of becoming bad debt because one or more of the payments are overdue. *For example, if one R10 payment on a R1000 loan is overdue, the entire R1000 is at risk and the entire R1000 should be included in the arrears figure presented here. If the Savings and Loans Division does not age arrears, please note that and provide the unaged figure.*

11. Branch Structure

	1996/1997	1997/1998	1998/1999	1999/2000
Total number of branches at beginning of the period				
Total number of branches at end of period				
Total number of satellite branches/ agencies at beginning of the period				
Total number of satellite branches/ agencies at end of period				

12. Staff Structure (If the Savings and Loans Division has a different staff structure then please use the blank rows to describe the structures filling in the relevant staff numbers in the blank columns)

12.1 Savings Mobilisation Staff

	1996/1997	1997/1998	1998/1999	1999/2000
Total number of senior managers at head office at beginning of period				
Total number of senior managers at head office at end of period				

	1996/1997	1997/1998	1998/1999	1999/2000
Total number of managers at head office at beginning of period				
Total number of managers at head office at end of period				
Total number of administrative staff at head office at beginning of period				
Total number of administrative staff at head office at end of period				
Total number of cleaning staff at head office at beginning of period				
Total number of cleaning staff at head office at end of period				
Total number of branch managers at beginning of period				
Total number of branch managers at end of period				
Total number of senior loan officers at beginning of period				
Total number of senior loan officers at end of period				
Total number of loan officers at beginning of period				
Total number of loan officers at end of period				
Total number of administrative staff at branches at beginning of period				
Total number of administrative staff at branches at end of period				
Total number of cleaning staff at branches at beginning of period				
Total number of cleaning staff at branches at end of period				

12.2 Loan Staff

	1996/1997	1997/1998	1998/1999	1999/2000
Total number of senior managers at head office at beginning of period				
Total number of senior managers at head office at end of period				
Total number of managers at head office at beginning of period				
Total number of managers at head office at end of period				
Total number of administrative staff at head office at beginning of period				
Total number of administrative staff at head office at end of period				
Total number of cleaning staff at head office at beginning of period				
Total number of cleaning staff at head office at end of period				
Total number of branch managers at beginning of period				
Total number of branch managers at end of period				
Total number of senior loan officers at beginning of period				
Total number of senior loan officers at end of period				
Total number of loan officers at beginning of period				
Total number of loan officers at end of period				
Total number of administrative staff at branches at beginning of period				
Total number of administrative staff at branches at end of period				
Total number of cleaning staff at branches at beginning of period				
Total number of cleaning staff at branches at end of period				

	1996/1997	1997/1998	1998/1999	1999/2000

Thank you for taking the time to complete the questionnaire

APPENDIX B - Lender Questionnaire

MONITORING AND EVALUATION FORM FOR NON-GOVERNMENT AND DEVELOPMENT FINANCE INSTITUTIONS

This questionnaire is aimed at assimilating information for the monitoring and evaluation component of the Commission of Inquiry into the Provision Rural Financial Services. **All information will be kept strictly confidential.**

Name of Institution ______________________________

Address ______________________________

1. **KEY INSTITUTIONAL CHARACTERISTICS**

1.1 Legal status of organisation ______________________________

1.2 Years branch has been in operation ______________________________

1.3 Date of the most recent balance sheet (DD/MM/YY)______________________________

1.4 Date of balance sheet previous to the most recent balance sheet ______________________________

1.5 Overall size parameters of organisation as the date of the most recent balance sheet:

DESCRIPTION	RANDS		DESCRIPTION	RANDS	
	End of previous reporting period	End of most recent reporting period		End of previous reporting period	End of recent reporting period
TOTAL ASSETS			TOTAL LIABILITIES		
Loan Assets (principal outstanding)			Deposits from clients		
Accounts receivable			Borrowings from banks		
Fixed Assets (at cost)			Borrowings from other commercial sources		
Accumulated depreciation			Borrowings from government		
Provision for bad debts			Borrowings from donors		
Cash on hand			Accounts payable		
Deposits in other institutions			Other liabilities (please specify)		
Investments in private securities			TOTAL EQUITY		
Equity investments in other entities			Accumulated earnings		
Other assets (please specify)			Share capital		

1.6 Income and expenditure for the most recent accounting reporting period:

DESCRIPTION	End of most recent reporting period	DESCRIPTION	End of most recent reporting period
REVENUE		EXPENSES	
Interest revenue from loans received in cash		Personnel expenses: Salary expense	
Interest revenue from loans due but not yet received, i.e. accrued interest		Fringe benefits expense	
Fee revenue from loans received as cash		Bonus expense	
Fee revenue from loans due but not yet received		Other personnel expense	
Interest revenue on deposits in banks		Purchase of consumables	
Interest revenue from investments in securities		Other administration expenses	
Grants in cash		Extraordinary expense	
Grants in-kind consumed		Depreciation expense	
Grants in-kind that are not consumed		Grants in-kind consumed	
Extraordinary revenue		Bad debt provision expense	
Other revenue (please specify)		Extraordinary write-offs	
		Interest expense on borrowing from commercial banks	
		Interest expense on borrowings from other commercial sources	
		Interest expense on borrowings from government	
		Interest expense on borrowings from donors	
		Interest expense on deposits from clients	
		Other expenses	
		Dividend paid out	

1.7 How is the level of provision for bad debts determined ? For example, is provision made for the entire amount of the of principal outstanding on loans with some principal and interest payments more than 90 days overdue ? Is provisioning set at some fixed proportion for loans that are in arrears ? Does the level of provisioning differ between secured and unsecured loans ?

1.8 Staff composition

DESCRIPTION		NUMBER	
		End of previous reporting period	End of most recent reporting period
Credit function	Loan officers		
	Credit support staff		
Management			
General support			
Deposit mobilisation function			
Other staff			
Total staff			
Number of branches			

1.9 Where are your branches situated in this province ?

2. CLIENT PROFILE

2.1 The following table refers to number of clients :

CLIENT NUMBERS	Previous reporting period	Most recent reporting period
Total number of clients at the end of the period		
Total number of borrowers at end of period		
Total number of savers at the end of period		

2.2 What are the most common types of clients that you have ? (farmer, hawkers, micro-business)

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2.3 What numbers of the rural (farm and non-farm) loans are:

	FEMALE	MALE	MALE AND FEMALE (MIXED)
Individual loans			
Group loans			

2.4 What numbers of the rural deposits (farm and non-farm) are:

	FEMALE	MALE	MALE AND FEMALE (MIXED)
Individual deposits			
Group deposits			

2.5 If you lend to groups, why is this and what criteria must borrowers wanting to establish a group meet ? Explain

2.6 If you lend to individuals and groups, or only individuals, why do you prefer this rather than lending just to groups ?

2.7 Do you prefer lending to women ? If so, why ?

3. **LENDING PORTFOLIO**

3.1 List the loan products your organisation has to offer (if only a graduated loan scheme is offered, please list the loan graduations)

3.2 The following tables concern general aspects of your loan portfolio:

3.2.1 Total Portfolio

Total amount of principal and interest due in the most recent reporting period	
Total amount of principal and interest received in the most recent reporting period	

3.2.2 Loan disbursement figures for all loans

Number of loans outstanding at the start of the period (beginning of the most recent reporting period)	
Number of loans outstanding at the end of the period (end of the most recent reporting period)	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed during the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.2.3 Loan disbursement figures for all Agricultural Loans

Number of agricultural loans outstanding at the start of the period	
Number of agricultural loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of agricultural loans disbursed during the period	
Number of agricultural loans disbursed to first time borrowers	
Amount of principal disbursed in the period	

3.2.4 Loan disbursement figures for Seasonal Agricultural Loans

Number of seasonal agricultural loans outstanding at the start of the period	
Number of seasonal agricultural loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of seasonal agricultural loans disbursed during the period	
Number of seasonal agricultural loans disbursed to first time borrowers	
Amount of principal disbursed in the period	

3.2.5 Loan disbursement figures for Medium-Term Agricultural Loans

Number of medium-term agricultural loans outstanding at the start of the period	
Number of medium term agricultural loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed in the period	

3.2.6 Loan disbursement figures for Agricultural Land Purchases

Number of land purchase loans outstanding at the start of the period	
Number of land purchase loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.2.7 Loan disbursement figures for Non-Agricultural Land Purchases

Number of land purchase loans outstanding at the start of the period	
Number of land purchase loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.2.8 Loan disbursement figures for Loans to Women

Number of loans outstanding at the start of the period	
Number of loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.2.9 Loan disbursement figures for Loans to Groups

Number of loans outstanding at the start of the period	
Number of loans outstanding at the end of the period	
Number of borrowers in groups at the start of the period	
Number of borrowers in groups at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.2.10 Loan disbursement figures for Housing Loans

Number of loans outstanding at the start of the period	
Number of loans outstanding at the end of the period	
Amount of principal outstanding at the start of the period	
Amount of principal outstanding at the end of the period	
Number of loans disbursed in the period	
Number of loans disbursed to first time borrowers	
Amount of principal disbursed during the period	

3.3 The following tables refer to loan conditions and terms for loan products as listed in question 3.1 for the most recent reporting period:

LOAN PRODUCT	LOAN CONDITIONS	ESTABLISHED BORROWERS	FIRST TIME BORROWERS
	Maximum loan value (Rand)		
	Minimum loan value (Rand)		
	Maximum loan term (months)		
	Minimum loan term (months)		
	Average monthly payment		
	Typical time taken to repay loan		
	DIRECT COSTS:		
	Most common interest rate charged (nominal)		
	Fee charges (as a % of the loan amount)		
	INDIRECT COSTS:		
	Obligatory deposit as a % of loan size		
	Collateral as a % of loan amount		
	Typical number of visits by clients to lender's office		
	Typical time from application to approval (days)		

3.3 cont.

LOAN PRODUCT	LOAN CONDITIONS	ESTABLISHED BORROWERS	FIRST TIME BORROWERS
	Maximum loan value (Rand)		
	Minimum loan value (Rand)		
	Maximum loan term (months)		
	Minimum loan term (months)		
	Average monthly payment		
	Typical time taken to repay loan		
	DIRECT COSTS:		
	Most common interest rate charged (nominal)		
	Fee charges (as a % of the loan amount)		
	INDIRECT COSTS:		
	Obligatory deposit as a % of loan size		
	Collateral as a % of loan amount		
	Typical number of visits by clients to lender's office		
	Typical time from application to approval (days)		

3.3 cont.

LOAN PRODUCT	LOAN CONDITIONS	ESTABLISHED BORROWERS	FIRST TIME BORROWERS
	Maximum loan value (Rand)		
	Minimum loan value (Rand)		
	Maximum loan term (months)		
	Minimum loan term (months)		
	Average monthly payment		
	Typical time taken to repay loan		
	DIRECT COSTS:		
	Most common interest rate charged (nominal)		
	Fee charges (as a % of the loan amount)		
	INDIRECT COSTS:		
	Obligatory deposit as a % of loan size		
	Collateral as a % of loan amount		
	Typical number of visits by clients to lender's office		
	Typical time from application to approval (days)		

3.3 cont.

LOAN PRODUCT	LOAN CONDITIONS	ESTABLISHED BORROWERS	FIRST TIME BORROWERS
	Maximum loan value (Rand)		
	Minimum loan value (Rand)		
	Maximum loan term (months)		
	Minimum loan term (months)		
	Average monthly payment		
	Typical time taken to repay loan		
	DIRECT COSTS:		
	Most common interest rate charged (nominal)		
	Fee charges (as a % of the loan amount)		
	INDIRECT COSTS:		
	Obligatory deposit as a % of loan size		
	Collateral as a % of loan amount		
	Typical number of visits by clients to lender's office		
	Typical time from application to approval (days)		

3.4 Where does the client apply for a loan ? Does the loan officer visit the client, does the client come to the main office ? Explain

3.5 Where is the loan processed and approved ?

3.6 To what degree is the responsibility of loan approval assigned to the local branch manager or loan officer ? Is there a loan limit from where it has to be passed to a higher authority ?

3.7 How does the institution monitor whether or not borrowed funds are used for their stated purpose ?

3.8 Select the type(s) of collateral / collateral substitutes by loan product and difficulties in securing these (fill in the numbers corresponding to the appropriate statement, listed below the table, in the appropriate column. Should you have any difficulties in using the specified type of collateral in the event of foreclosure or for any other reason, please state what these difficulties are.)

LOAN PRODUCT	COLLATERAL / SUBSTITUTES				Most common problem you encounter
	First time borrowers		Established borrowers		
	Most common type of collateral	Newest type of collateral	Most common type of collateral	Newest type of collateral	
Seasonal agricultural loans					
Medium term agricultural loans					
Loans for agricultural land purchase					
Loans for non-agricultural land purchase					
Loans to women					
Group loans					

Key to filling in above table:
1 = Saleable product quota; 2 = Saleable crops and livestock; 3 = Accounts receivable; 4 = Term deposits and savings; 5 = Salary stop orders; 6 = Personal, physical and financial assets - 6.1 = Jewellery, 6.2 = Insurance policies, 6.3 = Shares, 6.4 = House; 7 = Third Party Guarantor - 7.1 = Relative, 7.2 = Business partner, 7.3 = Government guarantee, 7.4 = group guarantee; 8 = Credit track record; 9 = Long term business or family relationship; 10 = Threat of loss of future loans; 11 = Permission to occupy certificates; 12 = Land mortgage bonds; 13 = Provident fund; 14 = Employer guarantee; 15 = Crop cession; 16 = Character reference by village chief or respected member of community; Other (number sequentially and specify).

3.9 Does your institution apply a standard and rigid structure for loan repayments or are the repayment terms flexible in terms of amount repaid, duration of repayments etc. Is the repayment structure client or loan specific? Explain

3.10 Does a borrower qualify for a higher loan amount if the previous loan is repaid on time ?

3.11 Is there a maximum loan size which eventually forces successful clients to seek loans elsewhere ? Explain

3.12 If you lend to groups, are people in the groups allowed to borrow different amounts ? Explain

3.13 Other Services offered either by the branch or institution (please tick (✓) the appropriate box(es)):

Business training, technical production assistance		Other:	
Personal financial management			
Transmission services			
Financial planning			
Brokerage services			
Mobile banking services			

3.14 Do you charge individuals a partial or complete fee for any of the services offered in 3.13 ? Explain

____

____

____

____

4. LOAN COLLECTION AND ARREARS

4.1 Loan collection mechanisms (Please place a tick (✓) next to appropriate statement(s)):

Mail notices	________	Collection agency	________	Crop lien cessions	________
Personal visits	________	Borrower visits lender	________	Stop order	________

Other ____

____

4.2 Penalties for non-repayment of loans or incentives to encourage loan repayment

LOAN PRODUCTS	TYPES OF PENALTIES OR INCENTIVES
	a.
	b.
	c.
	a.
	b.
	c.
	a.
	b.
	c.
	a.
	b.
	c.
	a.
	b.
	c.
	a.
	b.
	c.
	a.
	b.
	c.

4.3 What criteria does the institution use, by loan product type, to define when a loan is in arrears ?

LOAN PRODUCTS	DEFINITION OF ARREARS

4.4 Loan portfolio repayment status (amount of principal and interest overdue)

AMOUNT OF PRINCIPAL AND INTEREST OVERDUE BY:	NUMBER OF LOANS		VOLUME (RANDS)	
	End of previous reporting period	End of most recent reporting period	End of previous reporting period	End of most recent reporting period
0-30 Days				
31 -60 Days				
61 - 90 Days				
+ 90 Days				

4.5 Loan portfolio repayment status (amount of principal outstanding for loans with some principal and interest overdue)

AMOUNT OF PRINCIPAL OUTSTANDING FOR LOANS WITH SOME PRINCIPAL AND INTEREST OVERDUE BY:	NUMBER OF LOANS		VOLUME (RANDS)	
	End of previous reporting period	End of most recent reporting period	End of previous reporting period	End of most recent reporting period
0 - 30 Days				
31 - 60 Days				
61 - 90 Days				
+ 90 Days				

4.6 What portion of the amount of the loan portfolio outstanding represents loans that have been rescheduled ? In general, a rescheduled loan may be defined as a loan for which the borrower missed one or more repayments but is not currently considered to be in arrears even though the borrower has yet to catch up on his/her repayments.

4.7 What criteria does the institution use to determine when a loan in arrears will be written off ?

4.8 Loans written off during the past two lending periods

Loan product	Number of loans written off		Amount written off (Rands)	
	End of previous reporting period	End of most recent reporting period	End of previous reporting period	End of most recent reporting period

5. FUND DEPOSITS - VALUES AND TRENDS

5.1 Deposit portfolio at end of last two accounting periods

TYPE	Number of active deposits		Total value (Rands)	
	End of previous reporting period	End of most recent reporting period	End of previous reporting period	End of most recent reporting period
FIXED DEPOSITS				
CORPORATE SAVINGS				
NOTICE DEPOSITS				
SAVINGS DEPOSITS (no notice required prior to withdrawal) e.g. passbook deposits				
VOLUNTARY GROUP SAVINGS				
COMPULSORY DEPOSITS:				
Group deposits				
Individual deposits				
OTHER				

5.2 Characteristics of deposits for the most recent reporting period:

TYPE	Range in size of deposits		Most Common interest rate paid	Amount deposited during the period	Amount withdrawn during the period	Number of deposit transactions in the period
	Minimum	Maximum				
FIXED DEPOSITS						
CORPORATE SAVINGS						
NOTICE DEPOSITS						
SAVINGS DEPOSITS (no notice required prior to withdrawal) e.g. passbook deposits						
VOLUNTARY GROUP SAVINGS						
COMPULSORY DEPOSITS						
Group savings						
Individual savings						
OTHER						

5.3 Please list any fees charged and rules which apply to savings instruments:

TYPE OF DEPOSIT	FEES PER TRANSACTION (RANDS)	RULES (e.g. minimum balance, notice period, maximum number of withdrawals etc.)
FIXED DEPOSITS		
CORPORATE SAVINGS		
NOTICE DEPOSITS		
SAVINGS DEPOSITS (no notice required prior to withdrawal) passbook savings		
VOLUNTARY GROUP SAVINGS		
COMPULSORY SAVINGS		
Group		
Individual		
OTHER		

6. CLIENT INFORMATION SCREENING TECHNOLOGIES/SCORING MODELS

6.1 Are there any loans for which no physical/tangible collateral is required ? Explain

6.2 Does your institution employ a systematic loan tracing / monitoring system on a weekly or monthly basis for a selected clientele ?

6.3 Does the institution use separate formal credit scoring techniques to analyse borrower financial data for any of the loan types ? Identify which loan type(s) and briefly explain the technique

6.4 What three elements are weighted most heavily in your credit scoring for the loan types indicated in the table below?

LOAN PRODUCTS	THREE ELEMENTS WEIGHTED MOST HEAVILY

Key to element codes:
1 = Character; 2 = Education, skills and/or training; 3 = Credit history; 4 = Collateral--property; 5 = Collateral--moveable assets; 6 = Repayment capacity; 7 = Profitability; 8 = Tenure status; 9 = Part-time/Full-time farmer status; 10 = Steady job; 11 = Pensions; 12 = Other non-farm income.

6.5 How does the institution verify credit worthiness data in Table 6.4 ? (Please place a tick (✓) next to the relevant statement(s))

Reliable, credible references	____	Credit-rating agencies	____
Shared info with other creditors / credit institutions	____	Staff visits to potential clients	____
Relevant documents, deeds etc. brought to branch by client	____	Shared information with loan guarantors	____

Other ____

7. **INSTITUTION OPERATIONAL PHILOSOPHY, PROGRAMME OBJECTIVES AND MANAGEMENT INFORMATION/CONTROL SYSTEMS**

7.1 What are your client target market(s) ?

____

____

____

7.2 Does the institution have a specific mission statement ? ____

7.3 If yes, please state it

____

____

____

____

____

7.4.1 How is the branch manager evaluated / promoted within the organisation (If there are multiple criteria, how are they weighted)? Explain.

7.4.2 Are there any branch manager performance incentive schemes ? If yes, please state and explain the criteria used.

7.5.1 What criteria does the branch manager use to evaluate his principal loan officers ?

7.5.2 Are there any explicit bonus schemes to reward principal loan officers ? If yes, please state and explain the criteria used.

7.6 Are there any loan and deposit staff performance incentive schemes ? Explain.

7.7 Define the composition of the Board of Directors and briefly specify their backgrounds (speciality, profession, qualifications, experience etc.)

8. FUTURE FINANCIAL INNOVATION FOR RURAL CLIENTELE

8.1 What major factors (e.g. legal, information, cultural, infrastructure etc.) does this institution perceive as constraints to the provision of financial services to rural clients (by client type if possible) ? Explain

8.2 What are the major financial service needs by type of rural clientele (e.g. emergent farmers, former homeland rural households and micro-small and medium sized enterprises) that this institution perceives lenders most need to address in the next five years ? Explain

8.3 Which of these financial service needs does this institution have the capability to address in the next five years (e.g. savings mobilisation etc.) ? How would this be done (i.e. what legal, information, infrastructure, education etc. constraints can this institution overcome or expects can be overcome) ?

THANK YOU FOR PARTICIPATING IN THIS SURVEY

Guidelines to Loan Data Requirements of the Score Card Development for MFO1

1. Introduction

This document describes in detail the data requirements for the development and validation of MFO1's scoring model. This document is to be used in conjunction with the electronic data sheet where the data will be recorded. A hard copy of the data sheet is provided in chapter two. The column names of the variables outlined in the Tables coincide with the column headings in the data sheet. It is recommended that the recording method of each variable is studied rigorously to avoid inconsistencies in the data as some of the data only applies to loans from MFO1 while some of the data is to be captured for all loans (this includes those loans which rejected MFO1 clients have obtained at other lenders). In addition, some of the data may be downloadable from the MFO1 data base while some data may have to be obtained from the loan application forms, MFO1 transaction view reports and the ITC client query reports. In all instances the recording method will clearly state where the data for the variable is obtained. Manual input of some data on loan histories and loans that MFO1 applicants have with other lenders may be beneficial and is deemed important in determining scoring variables concerned with the credit worthiness of the loan applicant and to verify the information on which the Empirica score is based. The following section briefly outlines the objectives of the study. This is followed by a definition of the inclusion and exclusion criteria of the sampling units, definitions of terminology and finally a detailed outline of the data to be captured in the electronic data sheet.

2. Objectives the Analysis

The objective of capturing the data are as follows:

1. To determine the factors influencing the credit granting decision of MFO1.
2. To determine factors influencing loan default amongst MFO1 clients.
3. To determine the effectiveness of the current in-house scoring system used by MFO1 to potentially improve the scoring system.

3. Applicant Account Selection Criteria

This section refers to the sampling criteria for MFO1 loans. The sample population consists of all loans applied for from 1 January 1999 to 20 November 1999. The sampling units are the individual loan applications of MFO1 and accepted loans of rejected MFO1 applicants at other lenders after the date of rejection at MFO1.

3.1 Inclusions

1. ALL FIRST TIME LOAN APPLICATIONS (both accepted and rejected) at MFO1 for the period 1 January 1999 to 20 November 1999 (this time period will be known as the window period). Clients with a pending, waiting and closed status on their accounts will considered provided they had been accepted on first-time application in the window period.
2. For REJECTED MFO1 loan applicants, all loans from other lenders which became active after the date of rejection at MFO1 will be included. This includes instalment accounts which were applied for and opened or opened after the date of rejection but before 30 May 1999. It applies to instalment accounts which were applied for and opened prior to the date

of rejection but which only became active after the date of rejection. It also applies to revolving accounts which were applied for and opened after the date of rejection but prior to 30 May 1999, and to revolving accounts which may have been opened prior to the date of rejection but which became active after the date of rejection but before 30 May 1999. To establish whether loans from other lenders meet these criteria it is necessary to identify all loans which became active in month after the MFO1 applicant was rejected.

3.2 Exclusions

1. All MFO1 applications prior to 1 January 1999 and after 20 November 1999.
2. For rejected MFO1 applicants, all loans from other lenders which had active payment profiles at the date of loan rejection at MFO1. All loans from other lenders with completed loan maturities prior to the date of rejection from MFO1.
3. For accepted MFO1 applicants, loans from other lenders.

4 Definitions

The tables identifying the variables and outlining the recording method will have four headings. These are variable name, variable description, column name and recording method. Please read items carefully before entering data into the data sheet. Where the recording method specifies a system entry, DO NOT record anything in the block for that particular column. The following definitions of terminology used throughout this chapter may be useful.

Sample loan	Refers to the loan which is entered as an observation on an individual row in the data sheet.
Variable name	Identifies the variable to be measured.
Column name	Refers to the name of the column in the data sheet.
Payment profile	Refers to the recording of the borrowers monthly repayment on the ITC client enquiry report.
Enquiry history	Refers to the documented number of enquiries an individual made at various lenders on the ITC client enquiry report.
Repayment performance	Refers the timeliness of the borrowers loan repayment
Account	Refers to the loan applicants loan account or loan.

5. Data Recording Method

The columns will each have a name. Where applicable enter the data in the correct block for that column.

Each account which is included under the inclusion criteria in section 3 is entered on a separate row in the data sheet. However all loans for a particular MFO1 client must be retained under one account number. This also applies for loans from other lenders which are recorded for rejected MFO1 applicants. Table 1 provides an example (note: the codes for Table 1 are found in section 6).

Table 1 Example of Data Sheet

Account Number for loan at MFO1	Loan number for MFO1 loans only	Lender Identification	Loan Identification	Accept or Reject

100704576	45879	1	1	1
	56790	1	1	1
100689273		1	2	2
		2	2	1 (note this individual was rejected by MFO1)
100367099	78905	1	3	1

6. Account and Loan Identification Data

This section records the variables which will be used to identify accounts and loans for sorting purposes in the data sheet.

Table 2 Variable descriptions falling under General

	Description
Variable Name	Account number
Variable Description	MFO1 account number of client
Column Name	Account number
Recording Method	1. This may be a system entry but can also be obtained from the MFO1 transaction view report. 2. Record the account number of the sample client for each of the accepted and rejected loans in the sample.
Variable Name	Loan number
Variable Description	This variable records the MFO1 loan number. This is not applicable to rejected applicants and sample loans from other lenders.
Column Name	Loan number
Recording Method	1. May be a system entry but can be obtained from the transaction view report. 2. Record the loan number for all loans disbursed by MFO1. Where the loan number is not applicable leave the block blank.
Variable Name	Lender identification
Variable Description	Records whether the loan is from MFO1 or another lender.
Column Name	Lender identification
Recording Method	Enter 1 if sample loan is from MFO1. Enter 2 if sample loan is from another lender.
Variable Name	Loan identification
Variable Description	This variable records a code that links all loans granted to a particular sample client.
Column Name	Loan identification
Recording Method	1. Each sample loan, whether accepted or rejected, will be assigned a code linking it to a particular client. This code starts from 0. Thus all applications (both accepted and rejected) from MFO1 and other lenders belonging to the same individual will be assigned the same code. For example, the first individual has three loans from MFO1 and 2 other loans which are classified as sampling units. All will be assigned the code 0.

Variable Name	Accept or Reject
Variable Description	This variable indicates the loan status.
Column Name	Accept or Reject
Recording Method	Enter the following codes to describe the variable: 1 if loan application was accepted. 2 if loan application was rejected. 3 if loan application was cancelled. 4 if the loan application is pending. 5 if the loan application is waiting. (Just insert a number which applies in the column)

7. Loan Description Variables

This section records the information of the loan characteristics

Table 3 Loan Characteristics

Variable Name	Date application
Variable Description	This records the date when the loan application was made.
Column Name	Date of Enquiry
Recording Method	1. MFO1 - For MFO1 loans refer to the enquiries section of the ITC client query report or from the application form. Identify the sample loans and record the dates that the loan enquiry was made. For repeat loans no enquiry may be lodged in which case the date of enquiry is the same as the date on which the loan was paid out. 2. Sample loans from OTHER LENDERS - refer to the enquiries section of the ITC client query report. For the sample loan under consideration identify and record the date on which the enquiry was made. If no enquiry date is given, leave this block blank.
Variable Name	Date of loan disbursement
Variable Description	For loans which were accepted, this records the date on which the loans were paid out. For rejected applicants, this records the date the loan was rejected (Date of rejection is only applicable to MFO1 clients).
Column Name	Date of loan disbursement
Recording Method	1. MFO1 - the date of loan disbursement is the date when the loan was actually paid out. This information is obtained from the MFO1 transaction view report. 2. Loans from OTHER LENDERS - the date of loan disbursement is the date when the account was opened. This information is available from the payment profiles of the ITC client query report.
Variable Name	Date of first instalment
Variable Description	Records the date on which the first instalment is due.
Column Name	Date of first instalment

Recording Method	1. For MFO1 enter the date that the first instalment of the sample loan is due. This information is available from the transaction view report (could also be a system entry). The format should be dd/mm/yy. 2. For sample loans from other lenders, enter the due date of the first instalment as the first day of which ever month the loan repayments start on the payment profile (It is assumed here that instalments are due on the first day of every month although this may not be the case).
Variable Name	Loan principal amount
Variable Description	Records the loan amount before finance charges (interest) that is paid out to the sample loan applicants if the loan is approved. For rejected MFO1 sample applicants this variable records the loan amount requested. For loans from other lender, for rejected applicants, this records the principal loan amount paid out.
Column Name	Loan principal amount
Recording Method	1. From the transaction view report for MFO1 clients record the loan amount paid out. 2. From the enquiry from record the loan amount requested by rejected MFO1 applicants. 3. For sample loans from other lenders enter the loan principal amount which is recorded as the opening balance in payment profile section of the ITC report.
Variable Name	Interest charges
Variable Description	Records the interest charges on the loan. Interest charged is not available for sample loans from other lenders. This variable is also not applicable to rejected loan applicants.
Column Name	Interest charges
Recording Method	1. From the MFO1 transaction view report record the amount of interest raised for all accepted sample loans from MFO1.
Variable Name	Total principal and interest
Variable Description	Is a summation of the principal and interest due on the MFO1 loan.
Column Name	Total principal and interest
Recording Method	System entry
Variable Name	Club fee
Variable Description	Records the additional club fee charges (if any) that are paid by MFO1 borrowers. This is not applicable to sample loans from other lenders and is also not applicable to rejected applicants.
Column Name	Club fee
Recording Method	1. The information is available from the transaction view report. 2. Record the total club fee charges for the sample loan.
Variable Name	Total loan amount due
Variable Description	Records the total amount payable to MFO1 by the sample applicant. This only applies to approved MFO1 loans
Column Name	Total loan
Recording Method	System entry

Variable Name	Loan term
Variable Description	Enter the repayment term, i.e. how many months the sample applicant has, to pay back the loan. Not applicable to rejected applicants.
Column Name	Loan term
Recording Method	1. For MFO1 sample loans the number of months the borrower has to repay the loan can be obtained from the transaction view report. It may also be available on the data base. Enter the loan term as the number of months the borrower has to repay the loan. For example, if the borrower has 4 months to repay the loan, then record 4 months. 2. For sample loans from other lenders the loan term is obtained from the payment profile information of the ITC report under the heading 'terms'. Record the number that is specified in the 'terms' field. Where this information is not given, the data field should be left blank.
Variable Name	Monthly instalments due for MFO1 loans
Variable Description	This variable records the monthly instalments due for MFO1 loans only. Each instalment is due on the first day of a calendar month. No penalty interest is charged for instalments paid on any day from the first to the 20 of a month. Not applicable to rejected loan applicants.
Column Name	Monthly instalment of MFO1 loan
Recording Method	System calculation
Variable Name	Monthly instalments of loans from other lenders
Variable Description	Records the monthly instalments payable by rejected applicants on loans obtained from other lenders after the date of rejection. Not applicable to rejected MFO1 loan.
Column Name	Monthly instalment of other loan.
Recording Method	1. Enter the monthly instalment amount which is obtained from the payment profile of the ITC client query report.
Variable Name	Monthly loan instalment
Variable Description	Records the monthly instalment of the sample loans
Column Name	Monthly loan instalment
Recording Method	System calculation
Variable Name	Loan type
Variable Description	This column identifies whether it is an instalment or revolving type loan. Not applicable to rejected applicants.
Column Name	Loan type
Recording Method	Enter 1 if the loan is an instalment type loan. Enter 2 if the loan is a revolving type loan.
Variable Name	Lender type

Variable description	Records the lender type from which the loan was taken. There are several lender types and this will be divided into the broad categories of furniture, building, clothing, retail, banking, MFO1, Other Micro-lenders, Jewellers, Other (if additional categories need to be specified then the necessary columns should be added and labelled appropriately). A classification of the different retailers given below. Not applicable to rejected loan applicants.
The grouping of the lenders is as follows (Please note that some of these lenders may belong to a holding company. Hence the enquiry may be listed under the holding company while the payment profile may be listed under one of the holding company's subsidiaries. A list of the group structures will accompany this document - see Appendix A). The abbreviations of the lender types indicated in parentheses will be used in the data sheet:	
Furniture (FUR)	OK Bazars, Geen and Richards, Savells, Tiptop furniture's, Bears, Joshua Doore
Clothing (CL)	Woolworths, Edgars, Foshini's, Milady's, Bee Gees, Smart Center
Building (BU)	
Retail (RE)	HUB, Game
Banking (BK)	Merchantile Bank, ABSA, Standard Bank, Wesbank, Stannic, Bankfin
MFO1 (MFO1)	MFO1
Micro-lenders (MI)	Consumer credit corporation
Consumber Credit Corporation (CC)	Consumber credit corporation
Jewellers	Galaxy, Sterns
Other lender types (Oth1)	Provides a column for an additional lender category not mentioned. Please name the column appropriately and specify the new lender type)
This list is not conclusive.	
Column Name	Lender type
Recording Method	This variable is a coded variable with the codes being as follows: Enter 1 if the sample loan is from MFO1 loan Enter 2 if the sample loan is a furniture loan Enter 3 if the sample loan is a building loan Enter 4 if the sample loan is a clothing loan Enter 5 if the sample loan is a general retail loan Enter 6 if the sample loan is a banking loan Enter 7 if the sample loan is from other micro-lenders Enter 8 if the sample loan is from jewellers Enter 9 if (for additional category add column and specify) Enter 10 if (for additional category add column and specify)
Variable Name	First time application or repeat loan
Variable Description	Records whether the sample loan application is a first time application at the respective lender or whether the account has already been established/opened
Column Name	First time application or repeat loan

Recording Method	Enter 1 for a first time application. Enter 2 for a repeat loan/established account.

8. Loan Repayment Performance Measures

Table 4 describes the variables used to determine loan repayment performance. Please note that some of this data will only be available for MFO1 clients who have a loan (This will be clearly indicated in the variable description column). Where MFO1 clients have loans with other lenders or where one is dealing with rejected or pending applicants some of this information required for this section is not applicable and hence the entries should be left BLANK. Please take note that the cur-off period (i.e. the time period at which the repayment status of all loans will be assessed) is 30 May 1999. The method of assessing loan repayment status will be as follows: The repayment status of all loans applied for and disbursed during the window period will be assessed as at this cut-off date.
This section records data on repayment performance.

Table 4 Loan Repayment Performance

Variable Name	Number of instalments actually made
Variable Description	This variable records the number of instalments the borrower actually made to repay the loan. Not applicable to loans from other lenders and rejected loan applicants.
Column Name	Number of instalments actually made
Recording Method	1. For MFO1 record the number of instalments actually made by the borrower to repay the loan. Where the loan was refinanced by DLP only count the instalments paid by the borrower. Do not count the DLP instalment.
Variable Name	Total amount paid at due date of each month (MONIN1...MONIN8) (MONIA1....MONIA8).
Variable Description	This variable records the monthly instalments actually paid by MFO1 sample clients only.
Column Name	Monthly instalments paid by MFO1 clients
Recording Method	1. The MFO1 data base will compute the total amounts paid by the sample client at two different cut-off dates. This first will be set to the financial month end which is the 20 of each month. The second will be set to the calendar month. Thus all payments made by the sample applicant as at the end of each financial month and calendar month will be recorded. This information will be used in an age analysis of the loan repayments to compute a payment profile of sample client and then classify the client in the various repayment categories. 2. TOINS1 (total instalments pd 1) and TOINS2 (total instalments pd 2) will record the total amount the borrower repaid for each of the monthly instalment computations.
Variable Name	Total loan repaid for instalments payable by 20th
Variable Description	Records the total amount of the loan repaid by the client for instalments payable by the 20 of each month

Column Name	Total loan repaid for instalments payable by 20th
Recording Method	System calculation
Variable Name	Total loan repaid for instalments payable by 30th
Variable Description	Records the total amount of the loan repaid by the client for instalments payable by the 30 of each month
Column Name	Total loan repaid for instalments payable by 30th
Recording Method	System calculation
Variable Name	Date loan was paid up
Variable Description	Records the date when the loan was completely paid-up.
Column Name	Paid-up date
Recording Method	1. For approved MFO1 loans enter the date on which the loan was finally paid up in the format dd/mm/yy. If the loan was not paid-up by the cut-off date enter the cut-off date of 30 May 1999 as the date when the loan was paid-up. If the loan has been classified as bad debt by MFO1 or referred to collections, then leave this data block blank.
Variable Name	Date loan was handed over to bad debt
Variable Description	Records the date on which MFO1 classified the loan as bad debt.
Column Name	Date loan was handed over to bad debt
Recording Method	1. If in the transaction view report, the loan was classified as bad, then record the date at which this was done in the format dd/mm/yy.
Variable Name	Amount refinanced
Variable Description	Records the DLP instalment amount paid by MFO1 to clear the borrower's current loan outstanding. This variable is only applicable to sample clients from MFO1 who have loans.
Column Name	Amount refinanced
Recording Method	1. Enter the Rand amount of the instalment denoted "payment received DLP". This applies to every sample loan refinanced by DLP. If the loan was not refinanced by DLP, then record a 0 in the space provided. 2. For loans where this is not applicable leave the data block blank.
Variable Name	Early settlement discount
Variable Description	Records the early settlement discount received by MFO1 sample clients on timely repayment of the loan amount. This variable is only applicable to MFO1 sample clients who have been granted loans.
Column Name	Early settlement discount
Recording Method	1. Record the Rand amount of the early settlement discount received as indicated in the MFO1 transaction view report.
Variable Name	Interest on overdue account
Variable Description	Only applicable to MFO1 clients. Records the total amount of interest paid on overdue instalments.
Column Name	Interest on Overdue

Recording Method	1. Interest on overdue is obtained from the transaction view report. For each sample MFO1 loan record the total interest paid on overdue instalments.
Variable Name	Net interest payable
Variable Description	Records the net interest payable on the loan
Column Name	Net interest payable
Recording Method	System calculation
Variable Name	Total loan amount due adjusted for interest
Variable Description	The total loan amount due for MFO1 clients adjusted for interest.
Column Name	Total loan amount due adjusted for interest
Recording Method	System calculation
Variable Name	Repayment ratio
Variable Description	Records the loan repayment ratio for the MFO1 client
Column Name	Repayment ratio
Recording Method	System calculation
Variable Name	Interest overdue ratio
Variable Description	Ratio of interest on overdue to total interest due
Column Name	Interest overdue ratio
Recording Method	System calculation
Variable Name	Loan repayment status for MFO1 clients
Variable Description	This variable will record the loan repayment status of all MFO1 loans only as at the financial month end of MFO1
Column Name	Loan repayment status Current Arrears Default Bad Refinanced Rescheduled

Recording Method	Each repayment category will occupy a column. In each column record the following: 1. Enter 1 under CURRENT if all instalments of the sample loan were repaid within 20 days of the due date. Enter 0 for the rest, except if the loan was refinanced or rescheduled. If the loan was refinanced by DLP then enter 1 under DLP. If the loan was rescheduled enter 1 under rescheduled. 2. Enter 1 under ARREARS if, for loans with completed maturity, any instalment was paid within 21 and 65 days after its due date. Enter 0 in the other columns except where the loan was refinanced by DLP or rescheduled. Enter 1 under refinanced if a DLP. If the loan was rescheduled enter 1 under rescheduled. 3. Enter 1 under DEFAULT if for loans with completed maturity any instalment was repaid after 65 days of its due date. Enter 0 in the other columns except where the loan was refinanced by DLP or rescheduled. Enter 1 under refinanced if a DLP. If the loan was rescheduled enter 1 under rescheduled. 4. Enter 1 under BAD if no instalments had been paid on the loan or if it has been written off as bad by MFO1. Enter 0 under all the other columns. 5. The data entry for this section may be automated and no manual entry may be necessary except for the cases where the loan was refinanced by DLP or rescheduled.
Variable Name	Loan repayment status of all sample loans (MFO1 and Other lenders)
Variable Description	Records repayment status of all loans (both MFO1 and sample loans from other lenders). Loan repayment information will also be obtained in this section on the loans which rejected MFO1 clients subsequently took with other lenders. The repayment categories are grouped into not due, current, arrears, default and bad. Refinanced and rescheduled loans are ignored since this information is not available for loans with other lenders. Some loans from other lenders may not have reached loan maturity. The repayment status will be taken up the cut-off date of 30 June 1999. This will result in an upper bound on the repayment status being set (i.e. the loan repayment status can only get worse with this information not being available to for the analysis).
Column Name	Loan repayment status of all sample loans Not due Current Arrears Default Bad

Recording Method	The repayment information for loans with other lenders is obtained from the payment profile on the ITC client query report. For MFO1 loans the entry into this section will be a system entry. 1. Enter 1 under not due if the loan repayments on other loans were not due as at 30 May 1999 and 0 in the other repayment categories. 2. Enter 1 under CURRENT for all loans with a 0 or 1 in their payment profiles and 0 in the other repayment categories. 3. Enter 1 under ARREARS for all loans with at least a 2 but not higher in the payment profile and 0 in the other repayment categories. 4. Enter 1 under BAD for all loans with at least a 3 in the payment profile but not higher and 0 in the other repayment categories. 5. Enter 1 under DEFAULT for all loans with 4 or higher in the payment profile and 0 in the other repayment categories.
Variable Name	Method of payment
Variable Description	Applies to MFO1 clients only and records the method in which loans are repaid at MFO1. On the current system they are either recorded as cash or other.
Column Name	Method of payment
Recording Method	The information can be obtained from the MFO1 transaction view report. Enter 1 if cash. Enter 2 if other method of payment was used (even if the borrower only used other methods for part of the loan repayments).
Variable Name	Previous loan of MFO1 refinanced
Variable Description	Records whether the previous MFO1 loan of the client was refinanced
Column Name	Previous loan from MFO1 refinanced?
Recording Method	Enter 1 if the previous loan from MFO1 was not refinanced Enter 2 if the previous loan from MFO1 was refinanced

9 Borrower Personal Characteristics

This section deals with the personal characteristics of the borrower with the column names and descriptions being outlined in Table 4. The variables in this section should be available for both accepted and rejected applicants.

Table 4 Borrower Personal Characteristics

	Description
Variable Name	Gender of sample client
Variable Description	Records gender of sample client
Column Description	Gender of sample applicant
Recording Method	Enter 1 if sample client is male Enter 2 if sample client is female

Variable Name	Date of birth of client
Variable Description	Records the date of birth of the client
Column Name	Date of birth of sample applicant
Recording Method	Enter the date of birth of the client in the format dd/mm/yy
Variable Name	Race of applicant
Variable Description	Records the race of the sample applicants
Column Name	Race of sample applicant
Recording Method	Enter 1 in the column if the applicant is Black Enter 2 in the column if the applicant is Indian/Coloured Enter 3 in the column if the applicant is White
Variable Name	Language preference of sample client
Variable description	Records the language preference of the sample clients
Column Name	Language preference of sample applicant
Recording Method	Enter 1 if language preference is zulu Enter 2 if language preference is English Enter 3 if language preference is other (specify the language) Enter 4 if language preference is other (specify the language)
Variable Name	Marital Status
Variable description	Records the martial status of loan applicant at the time of application
Column Name	Marital status of sample applicant
Recording Method	Enter 1 if sample applicant was married Enter 2 if sample applicant was single Enter 3 if sample applicant was divorced Enter 4 if sample applicant was widowed Enter 5 of other (specify the marital status)
Variable Name	Exact location of residence
Variable description	Records whether the loan applicant has provided an exact location of the residence in the physical address. An exact location is defined as a home unit number or a street address.
Column Name	Exact location of sample applicant
Recording Method	Enter 1 if the sample loan applicant has provided a unit number, street number or employers physical address if he/she lives on the employer's property. Enter 2 if the sample loan applicant has stated that he/she lives near to a particular place or has only given a Post Office box address. Enter 3 if no address particulars are provided by sample applicant.
Variable Name	Home address of sample applicant
Variable description	Records first line of the sample loan applicant's address such as street name, unit number, place where residence is near to.
Column Name	Home address of sample applicant
Recording Method	Enter first line of the sample applicant's address specifying the most precise location of the applicant. (e.g. 23 Berg Street, near Vulindlela School)

Variable Name	Area/suburb where the sample loan applicant lives
Variable description	Records Area/ Suburb where the sample loan applicant lives
Column Name	Area/suburb where sample applicant lives
Recording Method	Enter the section/suburb where the loan applicant lives (e.g. Scottsville, Plessislaer, Willowton, KwaMashu, Azalea Location, Pietermaritzburg Central). For small towns where there are no suburbs enter the town name (e.g. Wartburg, New Hanover).
Variable Name	Town where applicant lives
Variable description	Records Town / District where the loan applicant lives
Column Name	Town/district of sample applicant
Recording Method	Enter the town or district where the loan applicant's residence is situated (e.g. Edendale, Pietermaritzburg, New Hanover, Cato Ridge).
Variable Name	Length of residence at current address
Variable description	Records the length of time that the applicant has been living at his/her current place of residence.
Column Name	Length of residence at current address
Recording Method	Enter the number of years the applicant has lived at his/her current residence.
Variable Name	Length of residence at previous address
Variable description	Records the length of time the applicant has been living at his/her previous place of residence.
Column Name	Length of residence at previous address
Recording Method	Enter the number of years the applicant has lived at his/her previous residence/address.
Variable Name	Ownership status of residence
Variable description	Records the home ownership status of the loan applicant.
Column Name	Ownership status of residence
Recording Method	Enter 1 if sample client owns the residence Enter 2 if sample client lives on employer's property. Enter 3 if sample client lives with parents. Enter 4 if sample client rents the premises. Enter 5 if sample client lives in location (MFO1 do not distinguish between a hostel and a location. It is thus imperative that the address of the applicant is carefully noted to be able to classify this category). Enter 6 if sample client lives in hostel.
Variable Name	Monthly rental payments
Variable description	Records the monthly rental payments if the applicant rents his/her residential premises.
Column Name	Monthly rental payments
Recording Method	Enter the monthly rental amount in Rand if the applicant pays rent otherwise record a 0.
Variable Name	Monthly bond repayments

Variable description	Records the monthly bond repayments if the applicant owns a house and has a monthly bond repayment
Column Name	Monthly bond repayments
Recording Method	Enter the monthly bond repayment in Rands if the applicant owns a house and has a monthly bond repayment, otherwise enter a 0.
Variable Name	Does the applicant have a home telephone
Variable description	Records whether the loan applicant has a home telephone
Column Name	Home telephone
Recording Method	Enter 1 if the applicant has provided a home telephone number. Enter 2 if the applicant has NOT provided a home telephone number.
Variable Name	Does the applicant have a contact telephone number
Variable description	Records whether the loan applicant has a contact telephone number
Column Name	Contact number
Recording Method	Enter 1 if the loan applicant has provided a contact telephone number. Enter 0 if the loan applicant has not provided a contact telephone number.
Variable Name	Post destination
Variable description	Records where the applicant has specified that the post is sent to
Column Name	Post destination
Recording Method	Enter 1 if the post is sent to the residential/physical address. Enter 2 if post is sent personal PO Box address. Enter 3 if post is sent to the "care of" (c/o) another individual. Enter 4 if post is sent to the applicant's employer. Enter 5 (for additional options add columns and specify).

10. Employment Details of Applicant

The employment details of the individual are captured by the variables outline in Table 5 below. Again take note that several variables are coded.

Table 5 Employment details of loan applicant

	Description
Variable Name	Employment details
Variable description	Records whether the client has provided the employment details upon application with MFO1 or not.
Column Name	Employment details of sample applicant
Recording Method	Enter 1 if the applicant has provided details of employment on the application form. Enter 2 if the applicant provided no details on current employment.

Variable Name	Employment status
Variable description	Records the whether the loan applicant was employed full-time or part-time or on contract at the current employer.
Column Name	Employment status of sample applicant
Recording Method	Enter 1 if the loan applicant is employed part time. Enter 2 if the loan applicant is employed full time. Enter 3 if the loan applicant is employed on contract. Enter 4 other (add an additional column and specify the employment status). Enter 5 other (add an additional column and specify the employment status).
Variable Name	Contract termination date
Variable description	If the applicant is employed on a contract basis then, in this column, record the termination date of the contract
Column Name	Contract termination date
Recording Method	Enter date of contract termination in the format dd/mm/yy. Where a contract termination date is not applicable, leave the space blank.
Variable Name	Employer name
Variable description	Records the name of the employer with the purpose of establishing whether the employer is involved in manufacturing, government, car service, hospital, etc.
Column Name	Employer name
Recording Method	Enter the name of the employer on single line (e.g. University of Natal, City Royal Hotel etc).
Variable Name	Section/Suburb where workplace is situated
Variable description	Records the section/suburb where the employer is situated.
Column Name	Suburb where employer is situated
Recording Method	Enter the suburb where workplace is situated on a single row e.g. Scottsville, Willowton, Plessilaer, Dalton. The suburb where the employer is situated may not always be provided in the address, especially if a postal address is given. In this case the employer should be located in the telephone directory, where a street address can normally be obtained. This can be used to locate the suburb on a map.
Variable Name	Town where workplace is situated
Variable description	Records town/ district where workplace is situated
Column Name	Town/district where employer is situated
Recording Method	Enter the name of the town or district in which the employer is situated on a single row (e.g. Pietermaritzburg, Edendale, Cato Ridge, Richmond).
Variable Name	Department where applicant is employed
Variable description	Records the department/division in which the applicant is employed.
Column Name	Department where sample applicant employed

Recording Method	Enter the department or division in which the applicant is employed in a single block.
Variable Name	Work description
Variable description	Records the type of work the applicant is involved in.
Column Name	Work description
Recording Method	Enter the work description of the applicant on a single block in the data sheet.
Variable Name	Telephone contact
Variable description	Records whether the applicant can be contacted by telephone at the workplace.
Column Name	Telephone contact at work
Recording Method	Enter 1 if no telephonic contact can be made with the loan applicant at work (has provided no telephone number or indicated that no telephonic contact can be made). Enter 2 if telephonic contact can be made but his contact is not immediate (a work telephone number is provided but the contact is not immediate). Enter 3 if telephonic contact at the work place is by message only. Enter 4 if telephonic contact at the work place is immediate.
Variable Name	Length of time employed at the current work place
Variable description	Records the length of time that the applicant has been employed at the current employer.
Column Name	Length of employment at current employer
Recording Method	Enter number that the applicant has been employed at the current employer. If the number of months is computationally difficult to enter, then enter the length of employment as number of years and months (yy/mm).
Variable Name	Length of time employed at the previous employer
Variable description	Records the length of time the applicant was employed at the previous employer.
Column Name	Length of the employment at previous employer
Recording Method	Enter number that the applicant has been employed at the previous employer. If the number of months is computationally difficult to enter, then enter the length of employment as number of years and months (yy/mm).
Variable Name	Net salary
Variable description	Records the net monthly salary of the applicant at the time of loan application.
Column Name	Net salary
Recording Method	Enter the net monthly salary in Rand.
Variable Name	Basic salary
Variable description	Records the basic monthly salary of the applicant at the time of loan application.
Column Name	Basic salary
Recording Method	Enter the basic monthly salary in Rand.

11. Details of Spouse/Closest Relative/Friend

Table 6 outlines the variables recording details of the spouse, closest relative or friend and forms part of the loan security provided by the applicant to MFO1. For rejected applicants some of this information is missing may influence the extent to which loan applicants are granted loans or are rationed by MFO1.

Table 6 Details of loan applicant's spouse, relative or friend

	Variable Description
Variable Name	Details present
Variable description	Records whether the loan applicant has provided the required details on the spouse, relative or friend.
Column Name	Spouse details present
Recording Method	Enter 1 if the loan applicant has not provided details of the souse, relative or friend (if these were simply not recorded by MFO1 for any reason other than the applicant not having provided the details leave this space blank). Enter 2 if the applicant has provided details of a spouse, relative or friend.
Variable Name	Relationship of the spouse, relative or friend to the loan applicant
Variable description	Records the relationship of the individual whose details are being recorded in this section to the client.
Column Name	Relationship to client
Recording Method	Enter 1 if the relationship to the applicant is specified as none. Enter 2 if a relative/aunt/uncle. Enter 3 if a sister/brother. Enter 4 if a parent. Enter 5 if a wife/husband.
Variable Name	Gender of spouse, relative or friend
Variable description	Records gender of the spouse/relative/friend
Column Name	Gender of spouse, relative or friend
Recording Method	Enter 1 if the spouse, relative or friend is a female. Enter 2 if the spouse, relative or friend is a male.
Variable Name	Employment status of spouse, relative or friend
Variable description	Records whether the spouse, relative or friend is employed or unemployed
Column Name	Employment status of spouse, relative or friend
Recording Method	Enter 1 if the spouse, relative or friend is unemployed (also enter 1 if spouse, relative or friend is a house wife). Enter 2 if the spouse, relative or friend is employed. Enter 3 if the spouse, relative or friend is self-employed.
Variable Name	Name of employer
Variable description	Records place of employment of spouse/relative/friend

Column Name	Employer name
Recording Method	Enter the name of the employer in a single block in the data sheet. Some confusion may arise if the spouse if self-employed. If the applicant is self-employed then write the name of the business. Where this is not given leave the block blank. If spouse, relative or friend is a housewife, then leave this column blank. If domestic worker, then leave column blank unless name of employer is given.
Variable Name	Address details of employer
Variable description **Column Name**	Records whether a physical or postal address has been provided for the spouse's, relative or friend's work place. Address details of employer
Recording Method	Enter 1 if the spouse, relative or friend's employer address is given as a post office box. Enter 2 if the spouse, relative or friend's employer's address is given as a physical address. Enter 3 if both are provided. Enter 4 if none are provided.
Variable Name	Section/Suburb where employer is situated
Variable description	Records the suburb in which the workplace of the spouse, relative or friend is situated.
Column Name	Section/suburb where work place is situated
Recording Method	Enter suburb name in a single block in the data sheet (e.g. Scottsville, PMB Central, Dalton). Note: for rural towns there may be no suburbs in which case enter the town name in this block. In some instances the section/suburb may not be given as a postal address is given. If this is the case, the address of the employer may be found in the telephone directory and suburb located on a map.
Variable Name	Town/district where employer is situated
Variable description	Records the town where the workplace of the spouse, relative or friend is situated.
Column Name	Town/district where employer is situated
Recording Method	Enter the town name where the applicant's spouse, relative or friend is employed in a single block in the data sheet (e.g. Pietermaritzburg, Edendale, Dalton, Wartburg).
Variable Name	Department where applicant's spouse, relative or friend is employed.
Variable description	Records the division/department in which the applicant's spouse, relative or friend is employed.
Column Name	Department where spouse, relative or friend is employed
Recording Method	Enter the division/department name in a single block in the data sheet (e.g. hospital ward, kitchen, teaching). For self-employed individuals record the type of work done or else leave blank.
Variable Name	Employment category
Variable description	Records category of employment of spouse, relative or friend

Column Name	Employment category of spouse, relative or friend
Recording Method	Enter 0 if the spouse, relative or friend is employed as an unskilled worker. Enter 1 if the spouse, relative or friend is employed as a skilled worker, or is self-employed.
Variable Name	Home telephone
Variable description	Records whether the spouse, relative or friend has provided a home telephone number
Column Name	Home telephone of spouse, relative or friend
Recording Method	Enter 1 if NO home telephone number has been provided. Enter 2 if spouse, relative or friend HAS provided a home telephone number.
Variable Name	Work telephone
Variable description	Records whether the spouse, relative or friend has a work telephone number.
Column Name	Work telephone of spouse, relative or friend
Recording Method	Enter 1 is spouse, relative or friend has no work telephone number. Enter 2 if spouse, relative or friend has a work telephone number.

12. Details of Co-signer

Table 7 outlines the information recorded on the loan applicants co-signer. It follows a very similar format to the previous section and should be completed in exactly the same manner.

Table 7 Details of loan applicant's co-signer

	Variable Description
Variable Name	Details present
Variable description	Has the applicant provided the details of a co-signer
Column Name	Details of co-signer
Recording Method	Enter 1 if the applicant has NOT provided details of the co-signer (if the details have been omitted for any reason other than the applicant not providing the details of the co-signer to MFO1, leave this column blank). Enter 2 if the applicant has provided details of the co-signer.
Variable Name	Gender of co-signer
Variable description	Records the gender of the co-signer
Column Name	Gender of co-signer
Recording Method	Enter 1 if co-signer is a female Enter 2 if co-signer is a male.
Variable Name	Exact location of residence

Variable description	Records whether the loan applicant has provided an exact location of the residence in the physical address of the co-signer. An exact location is defined as a home unit number or a street address.
Column Name	Exact location of co-signer
Recording Method	Enter 1 if the sample loan applicant has provided a unit number, street number or employers physical address if co-signer lives on the employer's property. Enter 2 if the sample loan applicant has stated that the co-signer lives near to a particular place or has only given a Post Office box address. Enter 3 if no address details are given.
Variable Name	Home address of co-signer
Variable description	Records first line of the co-signer's address such as street name, unit number, place where residence is near to.
Column Name	Home address of co-signer
Recording Method	Enter the street name, Unit number, near school etc. in a single block in the data sheet.
Variable Name	Section/suburb of co-signer
Variable description	Records the section or suburb where the co-signer lives
Column Name	Section/suburb where co-signer lives.
Recording Method	Enter the section/suburb where the loan applicant lives (e.g. Scottsville, Plessislaer, Willowton, KwaMashu, Azalea Location, Pietermaritzburg Central). For small towns where there are no suburbs enter the town name (e.g. Wartburg, New Hanover).
Variable Name	Town/district where co-signer lives
Variable description	Record the town where the co-signer is situated
Column Name	Town/district of where co-signer lives
Recording Method	Enter the town name in a single block in the data sheet (Pietermaritzburg, Edendale, KwaMashu, Cato Ridge).
Variable Name	Employment status of co-signer
Variable description	Records whether the co-signer is employed or unemployed
Column Name	Employment status of co-signer
Recording Method	Enter 1 if the co-signer is unemployed (also enter one if co-signer is a house-wife). Enter 2 if the co-signer is employed by somebody. Enter 3 if the co-signer is self-employed.
Variable Name	Employer name of co-signer
Variable description	Records the name of the employer of the co-signer.
Column Name	Employer name of co-signer
Recording Method	Enter the employer name in a single block in the data sheet. For domestic workers where no employer name may be given, enter domestic worker in this block. For house-wife leave this column blank. For self-employed individuals, enter a the business name otherwise leave this block blank.

Variable Name	Home telephone of co-signer
Variable description	Records whether the co-signer has a home telephone number
Column Name	Home telephone of co-signer
Recording Method	Enter 1 if co-signer has NO home telephone number. Enter 2 if co-signer DOES have a home telephone number.
Variable Name	Work telephone of co-signer
Variable description	Records whether the co-signer has a work telephone number
Column Name	Work telephone of co-signer
Recording Method	Enter 1 if the co-signer has NO work telephone number. Enter 2 if the co-signer DOES have a work telephone number.

13. Banking Details of Client

The banking details of the client can be obtained from the original application from which is completed by hand. The variables pertaining to the banking details are described in Table 3.8.

	Description
Variable Name	Banking details of sample applicant specified
Variable description	Records whether the loan applicant has a any form of bank account or not
Column Name	Bank account specified
Recording Method	Enter 1 if the applicant has no bank account Enter 2 if the applicant does have some type of bank account
Variable Name	Bank account type
Variable description	Records the type of bank account the loan applicant has
Column Name	Bank account type Savings, Cheque, Transmission, Credit Card
Recording Method	Enter a 1 in the column block of the types of banking accounts that the loan applicant has and 0 in those columns that are not applicable.
Variable Name	Bank Name
Variable description	Records the name of the bank at which the accounts are held
Column Name	Bank Name
Recording Method	Enter the name of the bank in one block provided on the data sheet.

14. Enquiry History of Applicant

Where as the information on applicant personal details is recorded only for the initial application at MFO1, the variables for the following sections must be recorded for each individual loan application. As time passes on, information on the enquiry history and loans with other lenders may change and it is imperative that this information documented as accurately as possible. Table 8 outlines information to be recorded in this section. The enquiry and previous loan history may require considerable work as this section can only be entered manually. All of the information in this section is obtained from the ITC records. Please note, if additional columns have to be added to accommodate a category of lender or any other specification that is not currently listed in the data sheet, add additional columns as required in the data sheet and name them accordingly.

Table 8 Variables outlining the enquiry history of the loan applicant at the time of loan application

Column Name	Description
Variable Name	Total enquiries
Variable Description	Records the total number of enquiries prior to the sample loan enquiry date as listed by ITC client query report.
Column Name	Total number of enquiries at application date: furniture, building, clothing, retail, bank, micro-lender, jewellers, other.
Recording Method	1. Enter the total number enquiries the sample applicant made before the date of enquiry of the sample loan by lender type. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts this may be more difficult since such accounts may have no new enquiries listed or may have been applied for a long time ago. In this case all enquiries prior to the date at which the account was opened (for repeat MFO1 and other instalment accounts) and the date at which the account became active (for active revolving loans) are to be listed.
Variable Name	Recent enquiry history
Variable Description	Records the total number of enquiries within 12 months of the sample loan application as listed by the ITC client query report by lender type.
Column Name	Number of enquiries made within 12 months of the application date: furniture, building, clothing, retail, banking, MFO1, other micro lenders, jewellers, other (add and name additional columns as necessary).
Recording Method	1. Enter the number of enquiries recorded on the ITC report that were made within 12 months of the sample loan enquiry date. This effectively means going back 12 months from 1 day prior to the sample loan enquiry date and counting all the enquiries made within this time period. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts this may be more difficult since such accounts may have no new enquiries listed or may have been applied for a

	long time ago. In this case all enquiries 12 months prior to the date at which the account was opened (for repeat MFO1 and other instalment accounts) and the date at which the account became active (for active revolving loans) are to be listed.
Variable Name	Date of most recent enquiry
Variable Description	Records the date of the most recent enquiry prior to the sample loan enquiry date.
Column Name	Date of most recent and second most recent enquiry
Recording Method	1. Identify the most recent and second most recent enquiry date prior to the sample loan enquiry date and enter the date in the format dd/mm/yy. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts this may be more difficult since such accounts may have no new enquiries listed or may have been applied for a long time ago. In this case the dates of the most recent and second most recent enquiry prior to the date at which the account was opened (for repeat MFO1 and other instalment accounts) and the date at which the account became active (for active revolving loans) are to be listed.
Variable Name	Date of oldest enquiry
Variable Description	Records the date of the oldest loan enquiry prior to the sample loan enquiry documented on the ITC report.
Column Name	Date of oldest enquiry
Recording Method	1. Identify the oldest enquiry date prior to the sample loan application/enquiry and enter the date in the format dd/mm/yy. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts the enquiry date is the date at which the account was opened (for repeat MFO1 and other instalment accounts) and the date at which the account became active (for active revolving loans).
Variable Name	Number of default judgements at application
Variable Description	Records the number of derogatory public records (judgements) against the applicant at the time of enquiry of the sample loan.
Column Name	Number of default judgements
Recording Method	1. Enter the number derogatory public records at the sample loan enquiry date. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts the enquiry date is the date at which the account was opened (for repeat MFO1 and other instalment accounts) and the date at which the account became active (for active revolving loans).
Variable Name	Date of judgement
Variable Description	Records the date of the most recent default judgement.
Column Name	Date of most recent default judgement
Recording Method	1. Enter the date of the most recent default judgement against the applicant at the sample loan enquiry date in the format dd/mm/yy. For established instalment accounts (re-

	applications) and revolving loan accounts this may be more difficult since such accounts may have been applied for a long time ago. In this case the date at which the account was opened (for instalment accounts) and the date at which the account became active (for revolving loans) is to be used. If there has been no judgement then leave this block blank.
Variable Name	Enquiry conversions
Variable Description	Records the number of enquiries prior to the sample loan enquiry that were converted into loans by lender type (i.e. which lenders granted applicants loans subsequent to the enquiry prior to sample loan application).
Column Name	Number of enquiry conversions prior to the sample loan application date: Furniture, Building, Clothing, Retail, Bank, Micro-lender, Jewellers, Other (add additional column and specify).
Recording Method	Recording this variable requires that the enquiry record be matched with the payment profiles: 1. Match the names of the lenders which appear in the enquiry record with those which appear in the payment profile. (Note: some lenders belong to different parent companies. Please consult the accompanying companies list in appendix B to make sure that the lenders given in enquiries belong to the same holding company). 2. Look at the date of the enquiry and the date on which the account was opened. If they are within reasonable proximity (up to 1 month - this can sometimes be longer) then the enquiry has been converted into a loan. However, both dates must be before enquiry date of the sample loan. 3. Record the number of enquiries per lender group which have been converted to loans. For established MFO1 and instalment accounts (re-applications) and revolving loan accounts this may be more difficult since no new enquiries may be registered or such accounts may have been applied for a long time ago. In this case the date at which the account was opened (for MFO1 and instalment accounts) and the date at which the account became active (for revolving loans) is taken as the date for assessing prior enquiries.
Variable Name	Recent enquiry conversions
Variable Description	Records the number of recent enquiries prior to the sample loan enquiry that were converted into loans by lender type (i.e. which lenders granted applicants loans subsequent to the enquiry prior to sample loan application).
Column Name	Number of enquiry conversions within 12 months of the loan application date: furniture, building, clothing, retail, bank, micro-lender, jewellers, other (add additional column and specify).
Recording Method	Recording this variable requires that the enquiry record be matched with the payment profiles (recent enquiries refer to enquiries made going back 12 months from the application date):

	1. Match the names of the lenders which appear in the enquiry record with those which appear in the payment profile. (Note: some lenders belong to different parent companies. Please consult the accompanying companies list in appendix B to make sure that the lenders given in enquiries belong to the same holding company). 2. Look at the date of the enquiry and the date on which the account was opened. If they are within reasonable proximity (up to 1 month - this can sometimes be longer) then the enquiry has been converted into a loan. However, both dates must be before the date of enquiry of the sample loan. 3. Record the number of enquiries per lender group which have been converted to loans. For established MFO1 and other instalment accounts (re-applications) and revolving loan accounts this may be more difficult since no new enquiries may be registered or these accounts may have been applied for a long time ago. In this case the date at which the account was opened (for MFO1 and other instalment accounts) and the date at which the account became active (for revolving loans) is to be used as the date from which one assess the enquiries.
Variable Name	Loan principal amounts of converted loans
Variable Description	Records the loan principal amounts of converted loans by lender type.
Column Name	Loan principal amounts of converted loans Lender type Loan principal amount
Recording Method	1. For those enquiries converted into loans record the lender type which approved the loan and loan principal amount which the lender approved. This information is available from the ITC sheet as the opening balance. 2. The lender types will be entered in the following code form: Enter 1 if loan from furniture lender Enter 2 if loan from building supplies retailer Enter 3 if loan from clothing retailer Enter 4 if loan from general retailer Enter 5 if loan from bank Enter 6 if loan from MFO1 Enter 7 if loan from other micro-lender Enter 8 if loan from jeweller Enter 9 if other (specify)
Variable Name	Enquiries of rejected applicants
Variable Description	Records the number of enquiries made by rejected MFO1 applicants at other lenders after the date of rejection
Column Name	Number of enquiries by rejected applicants at other lenders after the date of rejection at MFO1: furniture, building, clothing, retail, banking, micro-lender, jeweller, (other)
Recording Method	1. Record the number of enquiries made by the rejected MFO1 loan applicant at other lenders after the date of rejection. This

	is divided into the different lender types.
Variable Name	Loans approved after rejection
Variable Description	Records the number of loans approved after the date of rejection by lender type.
Column Name	Number of enquires at other lenders converted after the date of rejection at MFO1: furniture, building, clothing, retail, banking, micro-lender, jeweller, (other)
Recording Methods	1. Of those enquiries made by the rejected MFO1 client after the date of rejection, count the number which were converted into loans. This is achieved by matching the accounts opened in the ITC payment profile to the enquiries.

15. Repayment performance of ACTIVE Loans at the time of Loan Application

This section essentially looks at the loan repayment performance of other active loans that were disbursed prior to the specified period of time but which were still being repaid during the specified period of 1 February 1998 to 31 January 1999. All the variables come from the perspective of what were the number and status of other active loans at the time of loan application. Table 9 describes the variables and the recording method.

Table 9 Performance of Active Loans at the time of loan application

	Description and Explanation
Variable Name	Repayment Status of Active Accounts
Description	Records the repayment status of active instalment and revolving loans the sample applicant had at other lender at the time of application for the sample loan. Active accounts are defined as all those accounts which were actively being repaid at the time of application of the sample loan. Note for established MFO1 and other instalment loans as well as revolving loans the application date is taken to be the date the account was opened (for instalment loans) or the date the account became active (for revolving sample loans). It also includes those loan accounts which have been opened but where loan repayments only commenced after the sample loan enquiry date. For example a loan may have been opened at Edgars on the 14 January 1998 but the repayments are only due on the 1 April 1998. On the 4 February 1998 the sample applicant applied at MFO1. Hence the loan at Edgars would fall under the not yet due category.
Column Name	Repayment performance of active loans from other lenders at the sample loan application date:
	furniture, building, clothing, retail, banks, MFO1, other micro lenders, jeweller, other (create additional columns and specify).
	0 1 - 2 ≥3 not due
	Value of most serious delinquency
	Date of most serious delinquency
	Value of most recent delinquency

	Date of most recent delinquency
Recording Method	1. From the ITC client query report look at the payment profiles and establish whether loans that were disbursed prior to the sample loan enquiry date have reached maturity (were paid-up) or were closed for some other reason or not. Accounts that have been closed or stopped as indicated by the payment profile status codes (see appendix A) are to be ignored. 2. Establish which loan accounts are still being paid off at the sample loan enquiry date and which loan accounts at other lenders were opened prior to the sample loan enquiry date but where repayments only commenced after the sample loan enquiry date. Revolving accounts which have no active repayment are still classified as active since they can become active at any time. 3. Once the active accounts have been identified, the number of loans falling into the various repayment categories must be entered by lender type. 4. Repayment performance is assessed ONE month prior to the month in which the application of the sample loan was made. At the time count the number of loans that were not yet due, which were current (showed only 0 in the payment profile), which were 1 - 2 months in arrears (showed no greater than a 2 in the payment profile one month prior to month in which sample loan application was made), and greater or equal to 3 months in arrears (as for 2 months but the payment profile showed a 3 or greater). Loans are classified as NOT DUE if they were opened prior to the sample loan enquiry date but loan repayments commenced after the sample loan enquiry date. 5. Of all the revolving credit loans and all the instalment loans establish the most recent and most serious delinquency level from the payment profiles (record the number given in the payment profile). For example if a payment profile showed a maximum of 4 months in arrears one month prior the month in which the sample loan application was made, then enter a 4. If there are no counts in a particular category, then enter a 0. Enter the dates of the most recent and most serious delinquency levels of the revolving and instalment type loans in the format (mm/yy). If none of the active loans showed delinquency then leave this block blank.
Variable Name	Instalment values of active loans at the time of loan application
Variable Description	Records the lender type to which the instalment is due and the instalment amounts of the active loans that the applicant was repaying at the date of sample loan enquiry, as well as, the instalments of those loans which were not active at the time of loan application but which become payable during the repayment period of the sample loan.
Column Name	Instalment amounts of active loans from other lenders at the sample loan application date Value of instalment Lender type Instalment amounts of opened accounts but which are not active at sample loan application date

	Value of instalment Lender type (For additional instalments add columns and specify)
Recording Method	1. Enter the code (see previous section) for the lender type of the various instalment amounts the sample applicant was repaying and for those loans not yet due. 2. Enter the instalment amounts from the ITC client query reports for all the loans that the borrower was actively repaying at the time of the loan application where the instalment amount for instalment 1 must correspond with the lender type under instalment 1. 3. Enter the lender type per instalment for loans not yet due 4. Determine the instalment amounts of those loans not yet due but where the instalments become payable during the repayment term of the sample loan. For this identify those loans from the payment profile where the account was opened prior the date of the sample loan enquiry and where instalments on such accounts became payable during the repayment term of the current loan. This implies that the payment profile becomes active during the repayment period of the sample loan.
Variable Name	Loan principal amounts of active loans at the time of application
Variable Description	Records the loan principal amounts of the active loans and loans not yet due.
Column Name	Loan principal amounts of active loans by lender type at sample loan application date: Value of loan Lender type Loan principal amounts of opened accounts but which are not active at sample loan application date: Loan amount Lender type (For additional instalments add columns and specify)
Recording Method	1. Record the loan principal amounts of the loans for which the instalments were recorded in the previous variable

16. Loans with COMPLETED Loan Maturity

This section records data on all those loans which were closed/ paid up at the time when the application was made for the sample loan. Table 3.10 describes the variables and recording method of the data for this section.

Table 3.10 Data for COMPLETED loans (loans which have been paid-up)

	Description
Variable	Account status on loans closed/paid-up within the last 12 months of the sample application
Variable Description	Records the number of closed accounts for a given status category
Column Name	Total number loans closed within 12 months prior to the sample loan application date with the following status: absconded (A), closed (C), disputed (D), repossessed (J), handed-over (L), paid-up (P), returned mail (R), written-off (W).
Recording Method	1. From the ITC payment profile, identify all accounts which have been closed or stopped within a 12 month period prior to the date of enquiry, starting one prior to sample loan application date and going back 12 months. For repeat MFO1 loans and repeat instalment loans at other lenders the date of enquiry is taken as the date at which the loan account was opened. For active revolving accounts the application date is taken as the date at which the account became active. The status on the closed loans may vary and is given in code form by ITC (see Appendix A). 2. Enter the number of accounts which fall into the specified account status category. Where a particular lender category has no counts for a specified loan status, then record a 0 in that data block.
Variable	Account status on all loans closed/paid-up prior to the sample loan application date.
Variable Description	Records the number of closed accounts for a given status category
Column Name	Total number loans closed prior to the sample loan application date with the following status: absconded (A), closed (C), disputed (D), repossessed (J), handed-over (L), paid-up (P), returned mail (R), written-off (W).
Recording Method	1. From the ITC payment profile, identify all accounts which have been closed or stopped prior to the date of enquiry of the sample loan, starting one month prior to the sample loan application date and going back as far as the ITC report will permit. For repeat MFO1 loans and repeat instalment loans at other lenders the date of application is taken as the date at which the loan account was opened. For active revolving accounts the application date is taken as the date at which the account became active. The status on the closed loans may vary and are given in code form by ITC (see Appendix A). 2. Enter the number of accounts which fall into the specified account status category. Where a particular lender category has no counts for a specified loan status, then record a 0 in that data block.
Variable	Total number of loans closed within the last 12 months with the status J, L, W
Variable Description	Records the specified status for all accounts closed within 12 months of the sample loan application date by lender type
Column Name	Total number of loans closed within 12 months prior to the sample loan application date with the status J, L, W by lender type: furniture,

	building, clothing, retailers, banking, MFO1, other micro-lenders, consumer credit, jewellers, other.
Recording Method	1. From the ITC payment profile, for all loans identified as closed within a 12 months prior to the sample loan enquiry date, starting one month prior to the sample loan application date and going back 12 months, record the number of loans with the status J, L, or W for the various lender types. Where a particular lender category has no counts for a specified loan status, then record a 0 in that data block.
Variable	Total number of loans closed with the status J, L, W
Variable Description	Records the specified status for all closed accounts by lender type
Column Name	Total number of loans closed prior to the sample loan application date with the status J, L, W by lender type: furniture, building, clothing, retailers, banking, MFO1, other micro-lenders, consumer credit, jewellers, other
Recording Method	1. From the ITC payment profile, for all loans identified as closed prior to the sample loan enquiry date, starting one month prior to the sample loan application date and going back as far as the ITC report will permit, record the number of loans with the status J, L, or W for the various lender types. Where a particular lender category has no counts for a specified loan status, then record a 0 in that data block.
Variable	Total number of loans closed/paid-up within the last 12 months prior to the application date with the status A, R
Variable Description	Records the specified status for all closed accounts by lender type
Column Name	Total number of loans closed within 12 months prior to the sample loan application date with the status A, R by lender type: furniture, building, clothing, retailers, banking, MFO1, other micro-lenders, consumer credit, jewellers, other.
Recording Method	1. From the ITC payment profile, for all loans identified as closed within a 12 month period prior to the sample loan application date, starting one month prior to the sample loan application date and going back 12 months, record the number of loans with the status A or R for the various lender types. Where a particular lender category has no counts for a specified loan status, then record a 0 in that data block.
Variable	Total number of loans closed/paid-up prior to the application date with the status A, R
Variable Description	Records the specified status for all closed accounts by lender type
Column Name	Total number of loans closed prior to the sample loan application date with the status A, R by lender type: furniture, building, clothing, retailers, banking, MFO1, other micro-lenders, consumer credit, jewellers, other.
Recording Method	1. From the ITC payment profile, for all loans identified as closed prior to the sample loan enquiry date, starting one month prior to the sample loan application date and going back as far as the ITC report permits, record the number of loans with the status A or R for the various lender types. Where a particular lender category

	has no counts for a specified loan status, then record a 0 in that data block.
Variable Name	Date of most recent payment profile status
Variable Description	Records the date of the most recent payment profile status
Column Name	Date of most resent payment profile status of closed/paid-up accounts at sample loan application date: absconded, closed, dispute, repossession, handed over, paid-up, returned, write-off.
Recording Method	1. Record the date in the format mm/yy of the most recent occurrences of the specified payment profile status for the loans identified above.
Variable Name	Repayment performance of loans closed/paid-up within 24 months prior to the sample loan application date and for all loans closed/paid-up prior to the sample loan application date.
Variable Description	This set of variables records the repayment status of loans with completed loan maturities, i.e. loans that are paid-up at the date of application of the sample loan as given by the ITC client query report or which have been stopped for any other reason.
Column Name	Repayment performance of loans which were closed/paid-up within 24 months prior to the sample loan application date by lender type:
	Furniture, Building, Clothing, Retail, Banking, MFO1, Other Micro-lenders, Consumer Credit, Jewellers (for additional categories add columns and specify lender type)
	0 1 - 2 ≥ 3
	Repayment performance of all loans with completed loan maturities which were closed/paid-up prior to the sample loan application date by lender type:
	0 1 - 2 ≥3
	Date of most recent loan (mm/yy) delinquency
	Value of most recent delinquency
	Date of most serious delinquency (mm/yy) delinquency
	Value of most serious delinquency
Recording Method	1. Identify the payment profiles of all loans that were paid-up or closed at the date of enquiry of the sample loan. These should already have been identified following the data requirements above (except the time span is different for the two sections of this variable). Note: this variable has two sections. The first records the repayment profiles of all loans closed or paid-up within a 24 month period of the sample enquiry date and the second records the repayment profiles of all the loans, going back as far as the ITC report will permit, closed/paid-up at the sample loan enquiry date. 2. Examine the payment profiles of these loans and count the number of loans per lender category that fall into the different repayment performance categories and insert this number into the respective columns. 3. Repayment performance is assessed on the basis where payment profiles of completed loans which show no worse than a 0 on the payment profile fall into the (0) category, loans which show no

	worse than a 2 fall into the 1 to 2 category, loans which show a 3 or worse fall into the ≥3 category. 4. Of all closed/ paid-up loans establish the most recent and most serious delinquency level from the payment profiles (record the number given in the payment profile). If the loan had no delinquency then record a zero. Enter the dates of the most recent and most serious delinquency levels in the format (mm/yy). If there are no delinquency levels, leave this column blank.
Variable Name	Loan principal amounts of all closed/paid-up loans
Variable Description	Records the value of the loan principal of the closed/paid-up loans by lender type
Column Name	Loan principal amounts of all loans which have been closed/paid-up at sample loan maturity date: Loan Principal Amount Lender Type
Recording Method	1. Of all the loans which have closed/paid-up as identified in this section, record the loan principal amount and the lender type to which this loan principal amount applies.

17. Repayment Status of active OTHER loans at SAMPLE LOAN MATURITY

This section records the repayment status of other loans which the loan applicant (and now borrower) was actively repaying at the time of loan maturity of the sample loan. This section is important in tracking the financial management of the various loan accounts which the sample borrower may have during the sample loan repayment period. The layout is similar to the previous section except that time period at which the loan repayment performance of other loans is reviewed changes. Table 3.11 provides an outline of the data required and the recording method.

Table 3.11 Repayment status of OTHER loans at the time of Sample Loan Maturity

	Description
Variable Name	Repayment status of active loans from other lenders prior to the due of the first instalment of the sample MFO1 loan
Description	These variables record the repayment status of all active loans at the due date of the first instalment of the sample MFO1 loan. **Active loans are defined here has those loan accounts which are open and which have an active payment profile.** This includes all loans that began their repayment schedule prior to the sample loan enquiry date and which are not paid up by sample loan maturity date. It includes all loans which were active at the sample loan enquiry date and which became paid-up prior to the sample loan maturity date.
Column Name	Repayment performance of active loans from other lenders prior to the due date of the first instalment of the sample MFO1 loan by lender type:
	furniture, building, clothing, retail, banking, MFO1, other micro-lenders, consumer credit, jewellers (for additional lender types add columns and specify the lender type)
	0 (1 - 2) ≥3

Recording Method	1. Loans falling into this section must comply with the definition as stated in the variable description section. The repayment status of active loans from other lenders is assessed at one month prior to the due date of the first instalment. This information is provided by the payment profile of the ITC report. 2. Enter the number of loans falling into the specified repayment categories. 3. The specification is as follows: If the payment profile of the active loans from other lenders have no more than a 0 in the entire payment profile one month prior to the instalment due date of the first instalment of the sample MFO1 loan, then the loan is classified as a 0. If the payment profile has no more than a 2 one month prior to the due date of the first instalment of the sample MFO1 loan, the loan is counted in the 1 - 2 category. If the payment profile has a 3 or greater in the payment profile one month prior to the date of the first instalment, the loan is counted in the ≥ 3 category. Where there are no counts for a particular category, enter 0 in the data block.
Variable Name	Repayment status of active loans from other lenders during the loan repayment period of the sample MFO1 loan
Description	These variables record the repayment status of all active loans during loan repayment period of the sample MFO1 loan. **Active loans are defined here has those loan accounts which are open and which have an active payment profile.** This includes all loans that began their repayment schedule prior to the sample loan enquiry date and which are not paid up by sample loan maturity date. It includes all loans which were active at the sample loan enquiry date and which became paid-up prior to the sample loan maturity date.
Column Name	Repayment performance of active loans from other lenders in the month of the final contracted instalment of the sample MFO1 loan:
	furniture, building, clothing, retail, banking, MFO1, other micro-lenders, consumer credit, jewellers (for additional lender types add columns and specify the lender type)
	0 (1 - 2) ≥ 3
	1. Loans falling into this section must comply with the definition as stated in the variable description section. The repayment status of active loans from other lenders is assessed during the repayment period of the sample MFO1 loan. This information is provided by the payment profile of the ITC report. 2. The repayment performance is assessed from the month of the first instalment of the sample MFO1 loan to the month of the last contracted instalment of the sample MFO1 loan. Count and enter the number of loans falling into the specified repayment categories in this time period. 3. The specification is as follows: If the payment profile of the other active loans have no more than a 0 in their payment profile during the loan repayment period of the sample MFO1 loan, then the loan is classified as a 0. If the payment profile has no more than a 2

	during the repayment period of the sample MFO1 loan, the loan is counted in the 1 - 2 category. If the payment profile has a 3 or greater in the payment profile during the repayment period of the sample MFO1 loan, the loan is counted in the ≥ 3 category. Where there are no counts for a particular category, enter 0 in the data block.
Variable Name	Instalment amount of active loans at first instalment of MFO1 .
Variable Description	Records the instalment amounts of the active loans from other lenders the sample borrower was repaying at the first instalment of the MFO1 loan.
Column Name	Instalment amounts of active loans from other lenders at first instalment of the sample MFO1 loan: Instalment amount Lender Type
Recording Method	1. For each active loan identified in the previous variable, record the instalment amount and the lender type to which that instalment belongs in the data block.
Variable Name	Number of loans from other lenders opened prior to the first instalment of the MFO1 loan and which became active in the month of the first instalment.
Variable Description	Records the number of loans from other lenders that were opened prior to the date of the first instalment but which commenced repayment during or after the repayment period of the sample MFO1 loan.
Column Name	Number of loans from other lenders opened prior to the first instalment of the MFO1 loan, but which only became active during or after the repayment term of the MFO1 loan by lender type: furniture, building, clothing, retail, banking, micro-lenders, consumer credit, jewellers, other
Recording Method	1. Count the number of loans from other lenders which were opened prior to the due date of the first instalment of the sample MFO1 loan, which have not been closed off for any reason, and which either start their repayments during or after the repayment term of the sample MFO1 loan. For lender types which score no counts, enter a 0 in that data block.
Variable Name	Number of loans from other lenders opened during the loan repayment period of the MFO1 sample loan
Variable Description	Records the number of loans from other lenders that are opened during the loan repayment period of the sample MFO1 loan. These accounts may become active during the repayment period of the sample MFO1 loan or they may only become active after the repayment period of the sample MFO1 loan.
Column Name	Number of loans from other lenders opened during the repayment period of the sample MFO1 loan by lender type: furniture, building, clothing, retail, banking, micro-lender, jeweller, consumer credit, other.
Recording Method	1. Count the number of loans from other lenders which are opened during the repayment period of the sample MFO1 loan and which

	either start their repayments during or after the repayment term of sample MFO1 loan (starting from the month of the first instalment through the to the month of the last contracted instalment with MFO1). For lender types which score no counts, enter a 0 in that data block.
Variable Name	Loan repayment performance of loans from other lenders opened prior to or during the repayment period of the sample MFO1 loan (and which became active during or after the repayment period of the sample MFO1 loan) in the month of the final contracted instalment of the MFO1 loan by lender type:
Description	Records the repayment status of loans from other lenders which were opened during the repayment period of the sample MFO1 loan in the month of the last contracted instalment of the MFO1 sample loan. This means that the sample applicants began repaying these loans DURING or AFTER the repayment period of the sample loans. This would be indicated by a payment profile becoming active during or after the repayment term of sample MFO1 loans in the ITC report .
Column Name	Loan repayment performance of loans from other lenders opened prior to or during the repayment period of the sample MFO1 loan (and which became active during or after the repayment period of the sample MFO1 loan) in the month of the final contracted instalment of the MFO1 loan by lender type:
	furniture, building, clothing, retail, banking, MFO1, other micro-lenders, jewellers (for additional lender types add columns and specify the lender type)
	0 (1 - 2) ≥ 3. not due
Recording Method	1. Loans falling into this section must comply with the definition as stated in the variable description section. The repayment status of the opened accounts is assessed in the month if the final contracted instalment of the sample MFO1 loan. This information is provided by the payment profile of the ITC report. 2. For those loans which have become active, assess the repayment performance and count the number of loans by lender types which fall into the specified repayment categories and insert this number in the block provided. Count the number of loans which are open but which have not become active and insert this number in the not due column. 3. The repayment specification is as follows: If the payment profile of the active loans have no more than a 0 in the entire payment profile one month prior to the instalment due date, then the loan is classified as a 0. If the payment profile has no more than a 2 one month prior to the due date of the first instalment, the loan is counted in the 1 - 2 category. If the payment profile has a 3 or greater in the payment profile one month prior to the date of the first instalment, the loan is counted in the ≥ 3 category. If the loan repayments of loans from other lenders had not commenced during the repayment term of the sample MFO1 loan, the loan is counted as not due. Where there are no counts for a particular

	category, enter 0 in the data block.
Variable Name	Loan principal and instalment amounts of loans which were opened prior the due date of the sample MFO1 loans which became active during or after the repayment term of the sample MFO1 loan
Description	Records the principal and instalment amount of loans from other lenders which have been opened before loan repayment term of the sample MFO1 loan but which were not due prior to the first instalment of the sample MFO1 loan.
Column Name	Loan principal and instalment amounts of loans which were opened prior to the due date of the first instalment of the sample MFO1 loan and which became active during or after the repayment term of the sample MFO1 loan: Lender type Loan Principal Amount Instalment amount
Recording Method	1. Record the lender type and the corresponding loan and instalment amounts of loans as identified in the variable description section.
Variable Name	Loan principal and instalment amounts of loans which were opened during the repayment period of the sample MFO1 loan.
Description	Records the principal loan and instalment amounts of loans from other lenders which have been opened during the loan repayment term of the sample MFO1 loan.
Column Name	Loan principal and instalment amounts of loans opened during the repayment period of the sample MFO1 loan: Lender type Loan Principal Amount Instalment amount
Recording Method	1. Record the lender type and the corresponding loan and instalment amounts of loans as identified in the variable description section.
Variable Name	Number of loans from other lenders which were active in the month of the last contracted instalment of the sample MFO1 loan.
Description	Records the total number of active loans at the maturity date of the sample loan from MFO1.
Column Name	Number of loans from other lenders active in the month of the last contracted instalment of the sample MFO1 loan by lender type: furniture, building, clothing, retail, banking, micro-lender, jeweller, consumer credit, other.
Recording Method	1. Record the number of loans with active (repaying the loan) loan repayment profiles in the month of the last contracted instalment of the sample MFO1 loan.
Variable Name	Instalment amounts of all loans from other lenders which were active in the month of the last contracted instalment of the sample MFO1 loan.
Description	Records the instalment amounts of all active loans from other lenders in the month in which the sample loan from MFO1 became mature.
Column Name	Instalment amounts of all loans from other lenders active in the month of the last contracted instalment of the sample MFO1 loan: Instalment amount Lender type
Recording Method	1. Record the instalment amounts for loans identified in the previous variable.
Variable Name	New loan enquiries
Description	This variable captures all loans that were applied for (enquiries)

	during the repayment period of the sample loan.
Column Name	Number of new loan enquiries during the repayment period of the sample MFO1 loan by lender type: furniture, building, clothing, retail, banking, MFO1, other micro-lenders, jewellers, other (add columns and specify).
Recording Method	1. Identify all new applications/enquiries with other lenders during the repayment period of sample loans where the repayment period is taken from the date of enquiry up to and including the month of the last contracted instalment with MFO1. 2. Count the number of new enquiries during this period and record the number applications by lender type under the respective columns. Where no enquiries for a particular lender type record a 0.

Appendix D

Variables to be included in the Analysis of Loan Data

1. General Notes

- The period for analysis is defined as 1 January 1998 to 30 June 1999 (to coincide with the financial month of MFO1. All loans disbursed to clients during this period at the Pietermaritzburg branch are to be included in the analysis.

1.1 Has the loan application been accepted or rejected ______________________
(if the loan has been rejected, then go to section 3)

1.2 Client number ______________________

2. Loan Repayment Status of Accepted Clients

This section will have to be repeated for each loan disbursed to the client. Hence it is important to document the loan number for each client.

- Transaction view reports generated on the 3 June 1999 are required for each client.

2.1 Date of loan disbursement ________________
2.2 Date of first instalment ________________
2.3 Number of contracted instalments ________________
2.4 Number of actual instalments made ________________
2.5 Total principal paid (Rand) ________________
2.6 Total interest paid (Rand) ________________
2.7 Early settlement discount (Rand) ________________
2.8 Interest on overdue account paid (Rand) ________________

2.9 The following classification applies to each loan in the clients portfolio for the period under consideration:
The client may fall into one of the following repayment categories:

2.9.1 Loans that are up to date: ________________
(includes all loans which are not yet fully due but for which instalments due- or at least principal portion of instalments due- have been paid on time) - loans falling into this category will probably occur towards the end of the cut-off period

2.9.2 Loans without repayment problems ________________
(includes all loans with completed maturities where instalments have been repaid on time without being refinanced by DLP)

2.9.3 Loans which have been refinanced by DLP
Loans refinanced where instalments were paid:

Current ______________
2 - 14 days in arrears ______________
15 - 60 days in arrears ______________
Greater than 60 days in arrears ______________

2.9.4 Loans not fully due repaid with arrears

Loans not fully due, but where instalments (any) have been paid:
2 - 14 days after due date ______________
15 - 60 days after due date ______________

2.9.5 Loans with completed maturity repaid with arrears

Includes all loans that have been fully repaid where instalments were paid:
2 - 14 days after due date ______________
15 - 60 days after due date ______________

2.9.6 Loans which are in default

Includes all loans where instalments have been:
Paid more than 60 days after the due date ______________
No payment has been received ______________

The following includes documentation of the principal, interest and date of repayment which is supplementary to the above data (This may require manual data capture)

Value of Principal Payment

	Principal by Contract	Actual Amount Paid
Instalment 1		
Instalment 2		
Instalment 3		
Instalment 4		
Instalment 5		
Instalment 6		

Value of Interest Payment

	Interest by Contract	Actual Amount Paid
Instalment 1		
Instalment 2		
Instalment 3		
Instalment 4		
Instalment 5		
Instalment 6		

Date of Repayment

	Contract Date	Actual Date Repaid
Instalment 1		
Instalment 2		
Instalment 3		
Instalment 4		
Instalment 5		
Instalment 6		

3. Borrower Personal Characteristics

3.1 Gender (M/F) ____________
3.2 Date of birth/ID number (to get age) ____________
3.3 Language of preference of client ____________
3.3 Marital Status of Client (Married/Widowed/Single etc.) ____________
3.4 Place of residence:
Home address ____________
Section/Suburb ____________
Town/Area ____________
3.5 Length of residence at above address (years, months) ____________
3.6 Length of residence at previous address (years, months)
3.7 Does client
Rent house ____________
Own house ____________
Border ____________
Other (state) ____________
3.8 If client owns or rents house:
What are monthly rent/ bond repayments ____________
With which bank is bond held ____________
3.9 Does client have own telephone (yes/no) ____________
3.10 Does client have a contact telephone number (yes/no) ____________
3.11 Where is post sent to (home, work, postal) ____________

4. Employment Details

4.1 Employment status (full-time, part-time, casual, contract) ____________
4.2 If on contract, list contract termination date (dd-mm-yy) ____________
4.2 Details of current employer:
Company name ____________
Employer address ____________

4.3 Occupation of client
4.4 Category of employment (e.g. unskilled)
4.5 Department
4.7 Can client be contacted by telephone (yes/ no)
4.8 If yes, is contact immediate (yes, no, message only)
4.9 Length of employment at current employer (years/months)
4.10 Length of employment at previous employer (years/months)
4.11 Monthly income details:
Net salary (Rand)
Basic salary (Rand)
4.12 Gross monthly income (Rand)
4.13 Date when salary is paid

5. Details of Spouse/Parent/Closest Relative

5.1 Relationship to client (husband, wife, cousin etc.)
5.2 Home contact telephone number (yes/no)
5.3 Gender
5.4 Identification number (to get age)
5.5 Company name
5.6 Company Address:

5.7 Occupation category
5.8 Department in which employed
5.9 Can spouse be contacted at work by telephone (yes/no)
5.10 Income details of relative:
Net monthly salary (Rand)
Basic monthly salary (Rand)

6. Banking Details of Client

6.1 Does the client have a credit card or not (yes/no)
6.2 If yes to 6.1, what is the card type
6.3 If yes to 6.1 what is the expiry date
6.4 Does the client have other banking accounts (yes/no)
6.4 If yes to 6.3, what type of account is it:
Savings
Transmission

Cheque

6.5 Name of banking institution(s)

6.6 Branch(es) where account(s) is held

7. Loan Details of Client

7.1 Loan number

7.2 Date of loan application (dd-mm-yy)

7.3 Date of loan rejection (dd-mm-yy)

7.4 Date of loan approval (dd-mm-yy)

7.5 Loan amount requested (Rand)

7.6 Loan amount granted (Rand)

7.7 Interest rate charged (% per month)

7.8 Monthly instalment (Rand)

7.9 Date of loan disbursement (dd-mm-yy)

7.10 Total amount disbursed to borrower (Rand)
(This is amount is net of settlement of existing loans)

7.11 Method of payment (e.g. cash, cheque, money order, debit order, Post Office)

7.12 Loan approved by (e.g. senior assistant, branch manger etc)

7.13 Loan term (4 months or 6 months)

8. Details of Personal Reference

8.1 Gender

8.2 Home telephone (yes/no)

8.3 Address of reference:

8.4 Employer details

8.5 Work telephone (yes/no)

9. Previous Loan History of Client with Credit Indemnity

9.1 Is this a first time or repeat client

9.2 Has client made previous enquiries at MFO1 (yes/no)

9.3 If yes, then:

Enquiry number	Date of Enquiry	Reject by MFO1/ or not accept by client
1		

2		
3		
4		
5		
6		
7		
8		

9.4 If repeat borrower, then:

Previous loan no.	Date loan was taken	Loan amount	Repayment Status of Loan (current, refinanced arrears, default)*

* Please note the definitions of repayment status:
Current: if loans were settled with all instalments being paid on time
Refinanced: If loan was refinanced by DLP
Arrears: If loans were settled with instalments being paid 30 - 60 days or more after due date
Default: If loans were settled with instalments being paid 61 days or more after their due date

9.5 At the time of the current loan application, was borrower in repayment cycle of any other loan (yes/no) ________
If yes,
9.6 What is the amount outstanding on this loan (Rand) ________
9.7 What are the monthly instalments on this loan (Rand) ________
9.8 Is the loan repayment current/in arrears/ in default (according to definitions in section 2) ________

10. Loan History with Other Lending Institutions

- It would be useful to obtain an ITC printout which provides information on client loan history
- The list below, details information required on previous loan history of clients

10.1 Date of ITC Enquiry ______________________

10.2 Enquiry history of applicant

Enquiry no.	Date of enquiry	Lender where enquiry was made
1		
2		
3		
4		
5		
6		
7		
8		

10.3 Payment Profile on Loans:
(this will have to be repeated for every loan taken out)

10.4 Supplier of credit ______________________

10.5 Date account opened (dd-mm-yy) ______________________

10.6 Opening balance (Rand) ______________________

10.7 Instalment (Rand) ______________________

10.8 Current balance (Rand) ______________________

10.9 Repayment regime (e.g. monthly) ______________________

10.10 Date of first instalment (mm-yy) ______________________

10.11 Date of most recent instalment (mm-yy) ______________________

10.12 Number of instalments due so far ______________________

10.13 Number of instalments current ______________________

10.14 Number of instalments 1 month in arrears ______________________

10.15 Number of instalments 2 months in arrears ______________________

10.16 Number of instalments 3 months in arrears ______________________

10.17 Were the two most recent instalments in arrears ______________________

10.18 Empirica score (if any) ______________________

APPENDIX E

Data sheet for Borrower Case Files

Please complete the questions below as accurately as possible. Should you have any queries, please contact me at tel: (0331)-2605493.

1.1 Borrower Account Number : ______________________

1.2 Area Code : ______________________

1.3 Closest Town to Borrower: ______________________

2. **Loan Characteristics**

2.1 Date of loan application: ______________________

2.2 Date of loan approval: ______________________

2.3 Date of draw-down: ______________________

2.4 Loan amount (principal): ______________________

2.5 Insurance: ______________________

2.6 Assurance: ______________________

2.7 Stamp duty: ______________________

2.8 Total loan amount: ______________________

2.9 Base instalment : (principal and interest) ______________________

2.10 Insurance: ______________________

2.11 Assurance: ______________________

2.12 Total instalment amount: ______________________

2.13 Administration fee: ______________________

2.14 Frequency of repayments: ______________________

2.15 Loan term: ______________________

2.14 Date of first instalment: ______________________

2.15 Date of loan maturity: ______________________

2.16 Collateral required for loan:
(tick relevant block)

Unsecured (Life-a; Admission of Debt)
Crop cession
Permission to Occupy Certificate
Asset : machinery
Asset : building
Asset : livestock
Other (specify)

2.17 Loan purpose:
(tick the relevant block)

Maize
Potatoes
Sugar Cane
Livestock Production
Broiler Production
Machinery and Equipment Purchases
Machinery and Equipment Repairs
Irrigation Purchase
Other (please specify)

3. **Business Characteristics**

3.1 Type of business:
(tick the relevant block)

Farming
Contracting
Other (specify)

3.2 Is the operator starting a new venture :

Yes	No

3.3 Years of experience in running operation being financed (tick relevant block)

more than five years
two to five years
less than two years

3.4 Size of land holding: ______________ Ha

3.5 Area planted to crop: ______________ Ha

3.6 Is the crop irrigated ?

Yes	No

3.7 Extension services:

Adequate	Inadequate

3.8 Land tenure arrangements: (Explain)

____

____

____

____

3.9 Where does the borrower market goods produced: (tick relevant block)

Own consumption
Local community
Shops
Hawkers
Large organisations (Wholesalers, factories, etc)

3.10 Total value of assets at date of application R ______________

3.11 Total value of liabilities at date of loan application R ______________

3.12 Estimated income generated from operations: (per annum) R ______________

3.13 Total cost of operations (excluding A5 instalment) (per annum) R ______

3.14 A5 instalment including interest (per annum) R ______

3.15 Net income: R ______

4. Personal Characteristics

4.1 Borrower Age ______ years

4.2 Gender

Male	Female

4.3 Number of Dependants ______

4.4 Level of Education ______

4.5 Has the borrower done any additional courses which could assist him in running his business ?

Yes	No

4.6 If yes, please list these courses? ______

4.7 Present occupation ? ______

______

4.8 Present income

Source	Amount (R/month or annum, please specify)
Farm	
Other (specify)	

4.9 Is the borrower employed full or part-time in operations requiring finance?

Full Time	Part Time

4.10 Does the borrower employ someone else to manage his operations requiring finance:

Yes	No

4.11 If yes, is it family :

Yes	No

4.12 Where does the borrower make payments? ______________________

4.13 Approximate distance from borrower to where payments are made ? ______________________

4.14 Nearest branch to borrower? ______________________

4.15 Credit rating from credit bureau:

Good	Bad

4.16 Has the borrower previously had loans from A5 ? (Loans prior to the current loan)

Yes	No

4.17 If yes, were the loans repaid (cross relevant box)

Repaid, no problems
Repaid after maturity date
Loan written off

4.18 Has the borrower any other current loans with A5? (loans that matured during or after the year this loan was approved)

Yes	No

4.19 If yes, what amount is outstanding ? R ______________________

4.20 Has the borrower any current loans with other institutions ? (Loans that matured during or after the year this loan was approved)

Yes	No

4.21 If yes, what is the amount outstanding ? R ______________________

4.22 Number of visits of loan officer with client during duration of the loan : ______________________