CREDIT SCORING IN TERMS OF THE NATIONAL CREDIT ACT

L.E. GRYFFENBERG (B Com)
10521267

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Supervisor: Prof. A. Smit

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DEDICATION

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ABSTRACT

The new National Credit Act (NCA), of which the first two phases have already been implemented and of which the third and final phase will be implemented in full by 1 June 2007, will have a major impact on all credit providers in South Africa.

The microfinance industry has been subject to similar rules under the Microfinance Regulatory Council (MFRC) and therefore this segment of the finance industry can be used as an example of how to deal with the changes imposed by the NCA.

Of particular interest are the portions of the NCA regarding reckless lending, the imposition of interest rate ceilings and the establishment of a national credit register. Collectively these aspects create an environment for the application of credit scoring as a risk reduction tool.

A retrospective analysis was done using the loan data of a lender in the microfinance industry and from this data certain characteristics were identified which could be used to develop a credit scoring model.

Two score cards were developed from the research data and these were then deployed in a dual scoring matrix to combine their strengths.

The development data was then analysed in terms of these score cards and their relative effectiveness was measured with a receiver operating characteristic curve (ROC curve) and the Kolmogorov Smirnov test (KS test).

It is recommended that the manner in which characteristics is recorded on the credit application should be improved and that the improved information be re-evaluated at some point in the future to re-calibrate the scorecard which will improve its effectiveness.

It is also recommended that a formal credit policy should be deployed which should serve as a framework to improve the effectiveness of the credit scoring tool.

CHAPTER ONE

1. THE CHANGING FACE OF SOUTH AFRICAN CREDIT PROVISION

1.1. Introduction

This chapter provides insight into the background and rationale of the research topic; it introduces the problem statement and importance of the study and provides the purpose and aims of the research.

1.2. Problem statement

The new National Credit Act (NCA) is changing the face of credit provision in South Africa. All credit providers are facing new requirements imposed by the act and they now have to adapt their operational procedures to incorporate these.

There are three aspects of the new act which are important for the scope of this dissertation. Firstly these are the sections which deal with the granting of reckless credit, secondly the setting of interest and service fee ceilings and thirdly the establishment of a National Credit Register. The first aspect creates risk for the providers of credit while the second aspect reduces their ability to set their prices in a way which compensates for the risk. The third aspect gives credit providers access to information which can be used to reduce the risk contained in the first aspect while maximising their returns which is restricted by the second aspect. This can all be achieved by the application of credit scoring.

To mitigate the reduction in income due to the imposition of ceilings and to cover the additional administrative cost brought by the act, credit providers will have to find ways to reduce the risk in their credit portfolios. Fortunately the third aspect, the establishment of a national credit register, provides the basis to accomplish this. A broad based compulsory national credit register will give credit providers access to the information required to use credit scoring as a tool to properly assign risk to various clients. The credit register will also enable the credit provider to do a comprehensive affordability assessment, which is an excellent risk management tool in its own right.

Credit scoring is a combination of a consumer's historic behaviour with regard to credit and other geometric variables which has a statistical correlation with the propensity of a consumer to meet his/her financial obligations. Credit scoring will assist the credit provider in deciding when to grant credit and when not to and it will also help to determine whether a consumer is over-indebted, the curbing of which is the ultimate purpose of the act.

This dissertation explored how these measures, which have now become a statutory requirement in terms of the NCA, can be applied to not only meet the regulatory requirements but also to better manage the lender's risk.

1.3. Background for the study

Designed primarily to protect consumers from unscrupulous lending activities by creating a well-regulated credit economy, the NCA will ultimately replace the existing Usury Act of 1968, the Integration of Usury Laws Act 1996 and the Credit Agreements Act 1980. It will be phased in over a twelve-month period, starting on 1 June 2006 and coming into full force on 1 June 2007.

The expected impact that this act will have on the credit sector is summed up as follows by Debbie Carmichael, an associate at Deneys Reitz Attorneys when she said: "The credit sector of South Africa's financial services industry has undergone substantial reform as of 1 June this year, when portions of the National Credit Act took effect" (Carmichael, 2006). The act is aimed at eliminating reckless lending - where credit providers grant credit to consumers who are over-indebted. Should a credit agreement be considered reckless, the agreement may be suspended by a court of law while the consumer's obligations are restructured with the assistance of a debt counsellor or officers of the court (Carmichael, 2006).

It will require that business owners will have to conduct more stringent checks when granting credit to clients, to avoid being prosecuted for extending reckless credit. This will result in additional cost to the lenders which will have to be overcome by employing risk-based pricing for credit; this in turn should go a long way to ensure sustainability in the lending industry and it is one of the answers to the industry's quest to survive under the NCA. What it means is that microlenders should understand their clients and offer them credit that won't overburden them (Adams, 2006).

"The National Credit Bill will be released in a phased approach, so as to give business owners sufficient time to set up administrative and information technology systems that will assist in efficiently conducting credit checks," says Magauta Mphahlele (Adams, 2006), project manager of consumer law reform at the Department of Trade and Industry.

Phase one has commenced on the first of June 2006 with the establishment of the National Credit Regulator (NCR), which will register all credit providers as well as handle and investigate consumer complaints, research and education. The second phase saw the establishment of the National Consumer Tribunal (NCT) that will ensure credit bureau compliance and the establishment of a national credit register. This phase came into effect in September 2006.

After the enactment of the third phase (June 2007) business owners who grant credit to clients without conducting proper checks on the client's credit history, could face legal action if the client is unable to pay his/her debts. This will require business owners to thoroughly investigate each client's credit history to determine whether the client is able to make regular payments. Checks can be conducted by requesting proof of income, expenses, tax returns and other credit agreements, as well as suretyships. In the event of the court finding that the credit provider granted credit recklessly, the lender will forfeit the credit amount and all charges.

1.4. Purpose of dissertation

The NCA has not only brought new levels of consumer protection, it has also levelled the playing field in the credit provision industry and set the stage for effective credit scoring with the introduction of a National Credit Register. Because the microfinance industry was previously exposed to most of the concepts which are now embodied in the NCA it makes sense to use this industry as the yardstick of how to function within the parameters of these requirements.

The dissertation explored the concept of credit scoring and then developed a credit scoring model based on actual data obtained from a microfinance institution, which can be used by others as an example of how to go about setting up their own credit scoring model.

1.5. Conclusion

The NCA has changed the legislative landscape of credit provision and has established new levels of consumer protection which has an impact on the profitability of lenders. The Act also introduced the NCR which gives lenders access to more historic credit information on borrowers than ever before. These aspects create a suitable environment for the use of credit scoring by lenders.

CHAPTER TWO

2. MICROFINANCE, A WORKING EXAMPLE

2.1. Introduction

In this chapter it is proposed that the microfinance industry in South Africa can be used as an example of how to cope with the changes posed by the new NCA. At first the international acceptance of microfinance as a means to alleviate poverty is established and thereafter the growth of the microfinance industry in South Africa is reviewed. The concept that the regulation of the microfinance industry in South Africa acted as a catalyst to establish the NCA is then explored. From the aforementioned follows the logic that because the microfinance industry was previously regulated by similar rules to the NCA, that the experiences of the microfinance industry can be used as an example of how to comply with the new act. Thereafter a short analysis is done of the NCA followed by an overview of the concept of credit scoring.

2.2. Understanding the need for microfinance

Microfinance is accepted world-wide as an effective mechanism to extend financial services to the poor (Ledgerwood, 2000:3). There is growing evidence world-wide that microfinance works, and the challenge for the future lies in breaking down the walls between microfinance and the formal financial system (Littlefield and Rosenberg, 2004: 1).

In 1983 Muhammad Yunus established the Grameen Bank, a bank devoted to provide the poorest of Bangladesh with miniscule loans. It was an idea born in 1976 when he realised that poor people need credit to break the cycle of poverty. His solution is founded on the idea that credit is a fundamental human right, and that if poor people can borrow money on terms that are acceptable to them they will help themselves (Yunus, 2003:50). The microfinance philosophy as practised by the Grameen Bank is recognised internationally and Yunus was awarded the Nobel Peace Prize on 13 October 2006 in recognition of this. "Lasting peace cannot be achieved unless large population groups find ways in which to break out of poverty," the Nobel Committee said in its citation in Oslo, Norway. "Micro credit is one such means. Development from below also serves to advance democracy and human rights" (Hossain, 2006).

This concept is taken a step further by Prahalad (2005:10) when he illustrates that it is not necessary to lower prices to uneconomical levels to service the poor, instead the price performance envelope needs to be altered to package the goods or services in a way that the poor can afford. To understand the needs of the poor requires a radical mind shift by the more affluent.

The following example will illustrate:
A person needs a unit a day of a particular product to live. If one can buy in bulk you can save on the cost of packaging and distribution. Most people earn a monthly wage and therefore they are in a position to buy 30 units at a time which is a month's supply. The poor only earns a daily wage, he has to buy a single unit every day. The cost to supply a single unit is more than that of supplying a month's supply and therefore the poor ends up paying more for the product. The affluent looks at this and argues correctly that the poor could save money by rather buying the month's supply. However the poor does not have the means to do this as he lives from day to day. The argument of the affluent, though technically correct, shows a misunderstanding of the constraints the poor face when they make their purchase decisions. The poor has similar needs to the affluent, but to effectively serve them, one has to accept that a different cost paradigm exists.

This misalignment between wanting to protect the poor and not understanding their needs is evident in the way governments have used interest rate ceilings to protect the poor from predatory lenders. The result was the functional exclusion of the poor from financial services, as the regulated lenders were now unable to service the poor cost-effectively. Instead the poor were driven to informal lenders who did exploit them. Interest rate ceilings also result in the loss of transparency as lenders cope with the interest rate ceilings by adding confusing fees to their services (CGAP, 2004: 1).

Microfinance promises to serve the poor where traditional financial mechanisms have failed. However, if microfinance is not deployed in a responsible manner within a legislative framework that protects the poor, it has the potential to enslave the poor.

2.3. Microfinance as the catalyst for change in South Africa

In South Africa lending was governed by the Usury Act 73 of 1968 and the Credit Agreements Act 75 of 1980. Currently, for loans falling within the ambit of the Usury Act, the interest rate ceiling is set at 20% per annum for loans below R 10 000 and 17% for loans above R 10 000. CGAP (2004: 1) states that interest rate ceilings result in banks adding confusing fees to their services. Whitfield (2006: 16) and Peyper (2006) found that South Africa is one of the countries with the highest banking fees in the world. Another effect of interest rate ceilings is the exclusion of poor borrowers from financial services and in South Africa, 45% of our population does not have access to financial services (Finscope: 2005).

In 1994 the microfinance industry in South Africa was legitimised by Government with the publication of the exemption notice to the Usury Act in 1994. This was done to broaden the provision of financial services to economically disadvantaged people, who were at that time not being serviced by the traditional financial institutions. There was no regulation and the early days of the microfinance industry was characterised by very high interest rates and abusive practices.

This changed to a large extent after the introduction of the Microfinance Regulatory Council (MFRC) in 1999, as the industry evolved from its free for all early days into a more regulated and therefore stable one. This phase also saw the entrance of formal banks, new microfinance banks and other corporate role players participating in the sector (Seymour, 2005:1).

As the larger microfinance industry players started conforming to the MFRC regulations, they started questioning some of the practices they observed in other sectors of the finance industry. Retail finance and banking had fee structures that not only made it very difficult for the general public to compare for example the cost of credit provided by a furniture retailer to the cost of taking that same loan at a bank; they were also governed by separate acts which allowed them different mechanisms to hide the true cost of credit from the consumer. The result was the introduction of the NCA that "now regulates everyone who offers credit, including banks, retailers and microlenders", said Gabriel Davel, previously head of the MFRC and now the CEO of the new National Credit Regulator (Formby, 2006).

Davel, who was in charge of regulating microlenders for six years, said: "I came to the conclusion that there were problems in the mainstream credit market. Many of the people who were borrowing from microlenders should have been borrowing from banks." Davel estimates that between four and seven thousand credit providers will need to register in terms of the new act (Formby, 2006).

2.4. An overview of the NCA

The main purpose of the act is to prevent the reckless granting of credit, causing the client to become over-indebted. Amongst its provisions it can go so far as to set aside all of a consumer's obligations under a credit agreement. In other words, if a bank or other lender fails to take adequate cognisance of a client's financial position, including verification of income, living expenses, other obligations and existing debt, before lending him more money, the court could literally cancel the debt (Benetton: 2006).

The ten most important things governed by the NCA are summed up by Charlene Clayton (2006: 19) as follows:

- Better disclosure – The Act places specific obligations on lenders to disclose things like hidden fees and interest rates.
- Consumer information held by credit bureaus – The Act requires lenders to register all credit on a national register to enable lenders to do an affordability assessment. The Act also regulates credit bureaus with regard to consumer protection in terms of credit information.
- Unsolicited selling – The Act prohibits this practice.
- Marketing practices – The Act prohibits misleading advertising and negative option marketing.
- Reckless credit – The Act has mechanisms to deal with debt and create a safety net for those with too much debt, it also prohibits reckless credit and places an obligation on the lender to do an affordability assessment.
- The contract – The Act contains mechanisms to give the consumer access to an understandable contract.

- Interest rates – The Act considerably beefs up the disclosure of interest rates, fees and other charges and lays down a maximum rate of interest.
- Fees – The Act specifies what you may be charged when you enter into a credit agreement.
- Cost of Insurance – The Act seeks to regulate credit providers who sell insurance.
- Complaints – The Act regulates a new dispute resolution body namely the National Consumer Tribunal.

The NCA will be implemented in three phases. The more detailed overview which follows is based on the NCA, Act 34 of 2005, an extract published by the Mastermind Alliance (2006) and comments and observations by Mr Matthew Thorpe, a legal advisor in the microfinance industry.

<u>Phase 1 – 1 June 2006</u>
The sections of the NCA which took effect on 1 June 2006 deal with the interpretation, purpose and application of the Act *(Sections 1 – 12)* and the consumer credit institutions such as the National Credit Regulator (NCR) and other relevant bodies *(Sections 12 to 25 and 35 to 38)*.

<u>Phase 2 – 1 September 2006</u>
The sections which took effect on 1 September 2006 deal with the establishing of the National Consumers Tribunal (*Sections 26 to 34)* and confidentiality and personal information (*Sections 67, 68, 71 and 72)*.

The following sections deal with the National Credit Register and form part of the subject matter of this dissertation. In future all credit will have to be registered with the credit bureaus. This enables credit providers to establish a client's credit exposure better than ever before. One of the benefits will be that credit scoring will be more accurate, as all consumer credit information will be reported in a unified manner. It is important to note that if this key element is not effectively policed to ensure equal compliance between all role players, the NCA might very well be stillborn.

- **Section 69 -** Charges the National Credit Regulator (NCR) with establishing a National Credit Register.
- **Section 70** - Regulates how consumer credit information must be handled by credit bureaus.

Phase 3 – 1 June 2007

The sections taking effect on 1 June 2007 include consumer rights and consumer protection (*Sections 60 to 66)*, regulations on how credit providers are expected to operate and standards with regard to the advertisement of credit *(Sections 74 to 77).*

Sections 78 to 88 are of special importance for the purpose of this dissertation as they deal with over-indebtedness and reckless credit.

- **Section 78** - specifies where over-indebtedness and reckless credit does not apply, namely, where the consumer is a juristic person; a school loan or study loan; an emergency loan; a loan in public interest; a pawn transaction or an incidental credit agreement.
- **Section 79** - lays down the circumstances under which the Act will consider when a person is over-indebted.
- **Section 80** - specifies when a credit agreement will be regarded as reckless by the Act.
- **Section 81** - lays down the steps the Act requires a credit provider to perform to ensure that a credit agreement is not classified as reckless credit.
- **Section 82** - states that a credit provider may set criteria for themselves to comply with section 81, providing they are fair and objective; and that the NCR may also make available such models.
- **Section 83** - lays down the conditions under which a court may suspend a reckless credit agreement.
- **Section 84** - lays down the effect on a credit agreement if it is suspended by a court.

- **Section 85** - states that a court may declare a consumer as over-indebted and provide relief for over-indebtedness.
- **Section 86** - states that consumers may apply to debt counsellors to be declared as over-indebted and the actions the debt counsellor must then take.
- **Section 87** - lays down the conditions under which a magistrate court may re-arrange a consumer's debt.
- **Section 88** - lays down the effect of an order for debt review or re-arrangement for consumers and credit providers.

Sections 89 to 100 deal with consumer credit agreements.

The next section is also important for the purpose of this dissertation. *Sections 100 to 106* deal with interest charges and fees:

- **Section 100** – deals with forbidden costs.
- **Section 101** – regulates the cost of credit and defines the allowable charges.
- **Section 102** – deals with additional fees and costs allowable for specific types of credit agreements.
- **Section 103** – deals with interest and how it must be calculated.
- **Section 104** – deals with changes in interest, cost of credit and fees.
- **Section 105** – gives the minister the authority to set the allowable fees and interest rate. These were published by the minister in chapter five of the regulations to the NCA.
- **Section 106** – deals with credit life insurance.

Sections 107 to 123 deal with statements and changes to credit agreements. *Sections 124 to 133* deal with collection, repayment and surrender and debt enforcement.
Section 163 deals with agents and states that a credit provider's employees and agents must be trained in the matters to which the NCA applies.

2.5. The concept of credit scoring

How can lenders approve clients for credit within a few seconds? How does the bank decide what interest rate a particular client should get?

The answer is credit scoring.

A credit score can be defined as a number generated by a mathematical algorithm (a formula), based on information contained in the credit report of a large sample of debtors, which is a highly accurate prediction of how likely they are to pay their accounts.

Mark Schreiner (2000) describes a credit scoring model as a formula that puts weights on different characteristics of a borrower which has a bearing on how likely he/she is to perform in the repayment of the credit. The formula produces an estimate of the probability or risk that the credit will be repaid. The formula is derived by analysing data which reflects historic debtor performance and then finding specific characteristics which have a significant statistical correlation with credit repayment.

Credit scoring can also be described as a statistical technique that combines several financial characteristics to form a single score to assess a borrower's creditworthiness which can be used by credit providers as a guide in the credit-decision process (Wendel & Harvey, 2006: 1).

The terminology used in relation to credit scoring together with an explanation of what it entails follows.

- Credit scoring is a technique used to foretell, at the time of application, the probability of future repayment. It does not identify "good" (no negative behaviour expected) or "bad" (negative behaviour expected) applications on an individual basis, it provides odds or probability, that an applicant with a given score will be "good" or "bad" (Siddiqi, 2006:5).
- A scorecard is a model which consists of a group of characteristics statistically determined to be predictive in separating good and bad accounts (Siddiqi, 2006:5).
- A credit report or profile is a file containing a client's credit history; this file is kept up to date by a credit bureau which receives the credit information from credit

providers. The report contains information such as name, address, employer and ID number; these details are usually given when completing a credit application form. It also contains details on a client's credit history such as the payment profile and the history of his/her paying habits. A credit profile does not contain any discriminatory data such as race, sex or religious beliefs (Transunion ITC: 2006).

- A credit score is a number that lenders use to help them decide whether to give somebody credit or not. It is a tool which uses historic information on how a lender has interacted with credit in the past to predict how he will do so in future (Fair Isaac Companies, 2005:1). Most credit bureaus have such a credit score. In South Africa the credit scores of the two largest credit bureaus, namely Experian and TransUnion ITC are known as Delphi and Emperica respectively. A credit score is a snapshot of a client's credit report at a particular point in time; his/her credit score will change over time based on how he/she handles credit now and in the future. A bureau credit score is a very general measure and as such has certain shortcomings.
- A credit scorecard is the method employed to calculate a credit score. The scorecard is built by developing a model using statistical techniques and historical credit information of borrowers in the past to objectively predict the risk of default in the future. A high score shows that the risk on a borrower is low while low scores indicate high risk. The scores can also be divided into groups effectively ranking borrowers into risk bands regarding the possibility of their repaying the credit (Compuscan, 2006).
- An application scorecard is a specific type of scorecard used to categorise clients into risk bands. Each application scorecard will differ depending on the credit provider's specific risk management activities at the client level. It enables the credit provider with assigning credit limits, pricing and identifying the right collections strategy and it is based on the credit provider's own historic client data (Experian, 2006).

2.6. Conclusion

The South African government has recognised that microfinance has a legitimate place as a finance mechanism. Over time government has fine-tuned the legislation to further enable this mechanism. The latest episode in this effort is the introduction of the NCA which not only places microfinance in the mainstream of the economy; it also levels the playing fields between all providers of credit whilst at the same time protecting the consumer. This protection afforded by the NCA introduces a new element of risk to lenders. Credit scoring is a tool that can be used by lenders to estimate the probability that a borrower will service his debts and in doing so not only reduce their risk, but also satisfy the requirement the NCA to do an assessment of the borrower.

CHAPTER THREE

3. SCORING MODEL RESEARCH

3.1. Introduction

In order to determine which characteristics can be used to build a credit scorecard, a sample of debtors' loans were taken from the books of a prominent microfinance institution. The institution has requested to remain anonymous and therefore will be referred to as "The Lender". The debtors in the sample were given a definition as good, bad or indeterminate based on how they repaid their debt.

On the credit application The Lender records demographic information. From this demographic information characteristics were identified which could potentially be indicative of propensity to pay. These characteristics were then analysed to determine whether any statistical correlation exists between the characteristics and the propensity of debtors to repay their credit.

The next step in the process was based on information contained in the credit report of individuals which is held by the Credit Bureau. From the data on the credit report, a second list of characteristics was identified which could be indicative of a propensity to pay. These characteristics were also analysed to determine whether there was a statistical correlation between the characteristics and the propensity to pay.

These two sets of characteristics formed the basis of the scorecards that were developed; the scorecard development is described in chapter 4. The methodology that was applied in the development of these scorecards is described in detail by Naeem Siddiqi in his book Credit Risk Scorecards (2006).

3.2. Data types

The following types of data are useable when compiling a scorecard:

- Application data – this is gathered at the point of application and paints a picture of the applicant (for example age and place of residence).
- Bureau data – this is information held at the credit bureau (for example number of trades opened in the last 12 months).
- Behavioural data – this is information on the applicant repayment behaviour (for example the number of months in arrears).

3.3. Characteristics analysed

Two sets of characteristics were analysed. The first set was information contained in the credit application that clients completed when applying for a loan. This set was named the application characteristics. The second set was selected from the information contained in the credit report that is held by the credit bureau. This second set of variables was named the standard batch characteristics (SBC).

3.3.1. Application characteristics

The choices of application characteristics were restricted to the information that was contained on the credit application form of The Lender. From these the following variables were selected to be analysed:

- Loan reason
- Age
- Gender
- Marital status
- Number of dependants
- Bank name
- Bank account type
- Years at work
- Government employee (Y/N)
- Phone

- Mobile provider
- Residential postal code
- Address flag
- Residential province
- Employment province
- Same/Different residential and work postal code
- Next of kin relationship
- Car (Y/N)
- Own property (Y/N)
- Interested in buying property (Y/N)

3.3.2. Standard batch characteristics (SBC)

The standard batch characteristics (SBC) data is the payment profile information of consumers as hosted on TransUnion ITC's database. It consists of 320 variables that the bureau records for every individual who is credit active. It is a summary of an individual's credit life cycle. The variables are grouped into five categories namely:

- All trades (a trade is an individual's debtor's account with a merchant)
- Instalment trades (loan with a fixed instalment and term)
- Revolving trades (account with an open ended balance and a credit limit)
- Other trades (not included in the above two categories)
- General information

Within each of these categories, with the exception of general information, there is a standard list of variables for example: "number of trades", "number of active trades" and "number of satisfactory trades". The general information category includes variables such as "age", "gender", "number of judgements", "number of defaults", "age of youngest judgement" and "age of oldest judgement".

From these 320 the following variables were chosen to be analysed:

- Number of trades opened in the last 12 months
- Number of trades 3 months or greater past due
- Number of enquiries in the last 24 months

- Utilisation of open trades
- Ratio of current satisfactory trades to open trades
- Age of oldest trade (All)
- Number of defaults in the last 12 months
- Number of judgements in the past 24 months
- Number of satisfactory other trades
- Number of active revolving trades
- Number of trades
- Number of active trades
- Number of open trades
- Number of trades opened in the last 18 months
- Number of satisfactory trades
- Number of satisfactory trades 24 months or older
- Number of 6 months past due date statuses
- Number of trades currently 3 months past due
- Number of trades currently 6 months past due
- Number of write-offs
- Number of legal actions / collections
- Number of trades 3 months past due ever (W/O the payment profile)
- Number of trades 6 months past due ever (W/O the payment profile)
- Age of youngest enquiry
- Percentage of trades with 3 months or greater past due
- Age of youngest past due record
- Months since most recent 3 months or greater past due
- Total monthly payment
- Total balance
- Number of open instalment trades
- Number of instalment trades opened in the last 24 months
- Number of satisfactory instalment trades 24 months or older
- Number of instalment trades with 3 month past due date statuses
- Number of instalment write offs
- Number of instalment legal actions / collection
- Number of instalment trades 6 months or more past due

- Utilisation of all instalment trades
- Utilisation of open instalment trades
- Ratio of current satisfactory instalment trades
- Age of oldest instalment trade
- Age of youngest instalment trade
- Age of youngest instalment past due
- Age of oldest open instalment trade
- Total instalment credit limit
- Total instalment balance
- Number of active other trades
- Number of satisfactory instalment trades 12 months or older
- Number of other trades with 3 months past due statuses
- Number of other legal actions / collection
- Number of other trades with 3 months or more past due
- Utilisation of open other trades
- Age of oldest other trade
- Age of youngest other past due
- Age of youngest open other trade
- Total monthly other balance
- Total open other balance (Credit limit)
- Total other balance
- Number of revolving trades opened in the last 24 months
- Number of revolving write-offs
- Number of revolving trades 3 months or more past due
- Utilisation of all revolving trades
- Total revolving balance

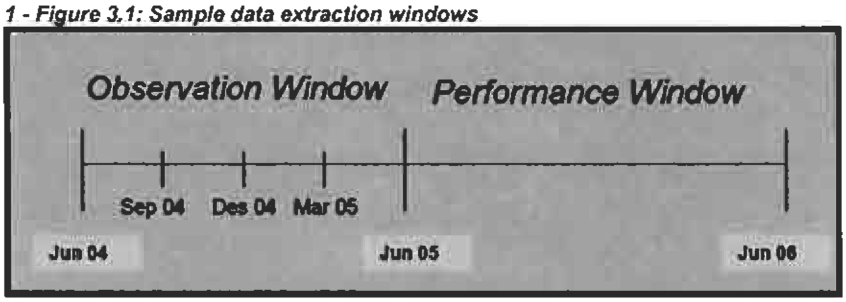
3.4. Data Summary

The following is a description of the loan data sample which was taken from the books of The Lender.

3.4.1. Time window

The time window consists of two periods. The first period is from 1 July 2004 until 30 June 2005 and is referred to as the observation window. The length of the observation window period of one year should eliminate any bias due to seasonal fluctuations. The second period consists of the performance window. The performance window of each loan starts at the date of approval and ends 12 months later. Figure 3.1 shows the longest possible performance window which would be for a loan issued right at the end of the observation window. Practically it means that the performance window has multiple brackets, starting when the loan is approved and ending 12 months later.

1 - Figure 3.1: Sample data extraction windows



3.4.2. Data sample and sample sizes

The data sample consists of all credit applications received by the lender in the observation window period i.e. 22 776 credit applications. This sample is referred to as the accept/reject sample.

Of these 22 776 applications in the accept/reject sample 8 166 were approved by The Lender and loans were disbursed; this portion of the sample is referred to as the development sample. The first 12 months of repayment history of each loan in the development sample were used to establish the performance criteria.

3.4.2.1. Extraction of the SBC data

The development sample data was divided into four sets for the extraction of the SBC data (listed in table 3.1). SBC data was extracted at the beginning of each period.

1 - Table 3.1: SBC data extraction dates

Set	Application Period	Extraction date
1	1 Jul 2004 – 30 Sep 2004	30 Jun 2004
2	1 Oct 2004 – 31 Dec 2004	31 Sep 2004
3	1 Jan 2005 – 31 Mar 2005	31 Dec 2004
4	1 Apr 2005 – 30 Jun 2005	31 Mar 2005

3.4.2.2. Filter Applied in the SBC Data Analysis

Of the total sample of 22 776 loan applications, 21 787 (96%) had a complete credit profile at the credit bureau. Of the development sample of 8 166 approved applications, 6 804 (83%) had a complete credit profile. The balance of 1 362 (17%) did not have sufficient information. The reasons for the latter were the following:

- 0.25% of the accounts had no bureau information at the time of extraction
- 13.53% of the accounts were inactive at the bureau at the time of extraction (i.e. no payment profile in the last 24 months)
- 2.89% of the accounts were too young at the time of extraction (first credit opened in the last 6 months).

Therefore these accounts were excluded from the data sample for the purpose of calculating the SBC variables.

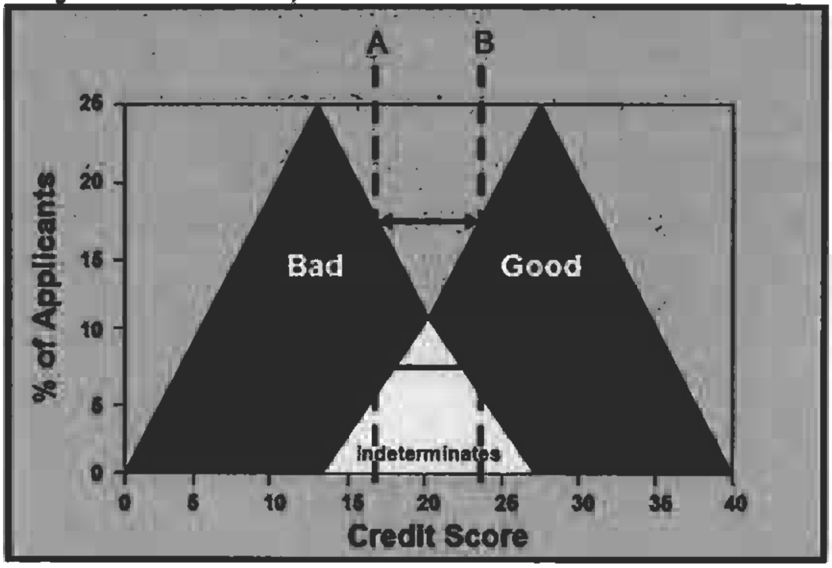
3.5. Key concepts

The following are key concepts which are used in the analysis.

- Odds:
  - Credit scoring uses odds to predict the probability of repayment.
  - Odds = number of good accounts / number of bad accounts.
  - For example: odds of 2:1 imply that from three accounts, one will be bad.

- Bad rate:
  - Bad Rate = number of bad accounts / number of bad and good accounts.
  - For example: 1/3 = 33.3% implies that from three accounts, one will be bad (which is equal to the odds of 2:1).
- Break-even odds:
  - If the average profit on a Good Account = R8 000 and the average loss on a Bad Account = R4000, then the break-even odds is R 8 000/R4 000 = 2.
  - Therefore if we are given three loans, we require one loan to be good in order to break even, which gives us a maximum allowable bad rate of 66.67% (2/3).
- Type I error:
  - This is the cost of classifying a defaulter as a non-defaulter i.e. the total credit cost of a loan not repaid.
- Type II error:
  - This is the cost of classifying a non-defaulter as a defaulter i.e. the profit lost as a result of these loan applications being rejected.
- Sensitivity and specificity
  - If the reduction of bad debt is the primary object of the development of a scorecard, the lender wants to lower the Type I error and maximise the "sensitivity". Sensitivity is the probability that a defaulter is correctly classified. In Figure 3.2, if line B is used as the cut point, it will result in reduced volumes and only high quality accounts will be accepted. Sensitivity is met and the total credit cost is minimised.
  - If growing the client base is the priority with the scorecard, the lender wants to lower the Type II error and maximise the "specificity". Specificity is the probability that a non-defaulter is correctly classified. In Figure 3.2, if line A is used as the cut point, the loan volumes will be maximised but low quality accounts will also be accepted. Specificity is met but the potential profit loss is still minimised.
  - Usually both of the above are major concerns and consequently the lender has to select a decision rule for classifying clients which results in the best mix of sensitivity and specificity. The cut point will be somewhere between line A and B (Figure 3.2) including more indeterminates.

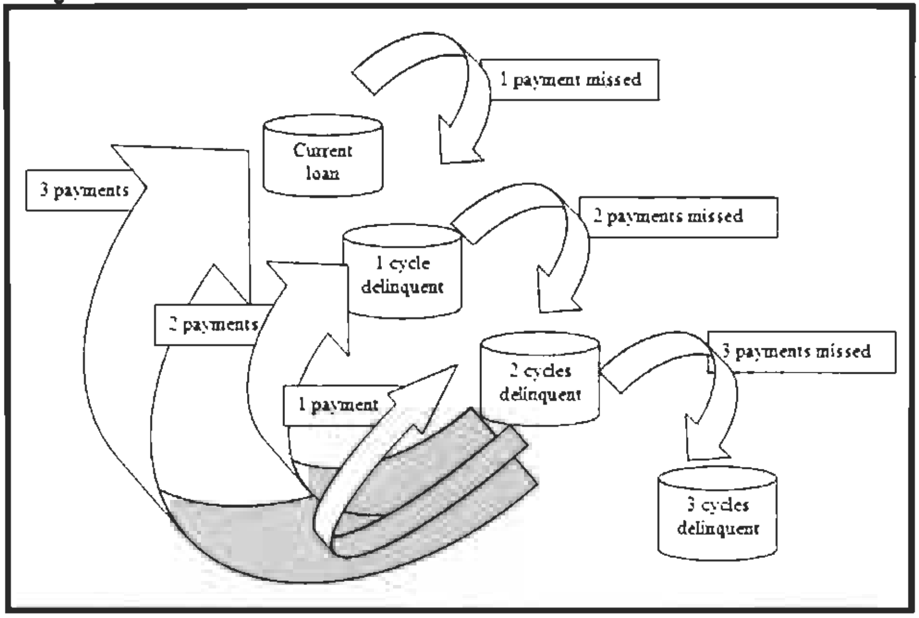
2 - Figure 3.2: Choice of cut points



- Delinquency
  - A delinquent cycle is when a loan is one payment in arrears.
  - Cumulative delinquency is the sum of delinquency cycles in arrears.
- Roll rate model
  - The classic roll rate model (as illustrated in Figure 3.3) is a structural model of the net rate at which accounts roll through delinquency stages, also referred to as buckets. Predictions are made by computing a moving average. A loan which is two cycles delinquent will roll to the third cycle delinquent bucket if no payment is made at the end of month two. If a single payment is made at the end of month two the loan remains in the second cycle delinquent bucket for another month. If two payments are made at the end of month two, the loan will roll back to the first cycle delinquent bucket.
  - There is a distinction between forward, static and backward roll rate. Forward roll rate is the most important and is when delinquency increases. Backward roll rate is a recovery and a static roll rate is where collections are constant.
- Reject Inference

  Application scorecards are developed to predict the behaviour of all applicants, and using a model based on only previously approved applicants will be inaccurate ("sample bias"). Therefore all applications received in the window period were also analysed using reject inference which is a method used to estimate the behaviour of previously rejected applications (Siddiqi, 2006:99).

3 - Figure 3.3: Classic roll rate model



3.6. Performance criteria

Two sets of performance criteria were used to analyse the data. The first criterion is the bad rate which is a product of the classification of loans as good, bad or intermediate based on their repayment history. The second criterion is the accept/reject rate which is derived from whether a loan was accepted or rejected by The Lender and is a result of the business rules applied by The Lender during the observation period.

3.6.1. Good, bad, indeterminate definitions

The roll rate model was used for classifying the delinquency cycle of the loans and the following definitions were applied:

- A good loan is defined as having a cumulative delinquency less than or equal to two months.
- A bad loan is defined as having a cumulative delinquency greater than or equal to four months.
- An indeterminate loan is defined as a cumulative delinquency equal to three months. This third definition is necessary in order for the best mix of sensitivity and specificity. A loan is deemed indeterminate, because it could be rolling forward or backward and it is difficult to establish in which direction it is rolling.

The distribution of the Good/Indeterminate/Bad accounts according to the definition is provided in Table 3.2.

2 - Table 3.2: Distribution of Good/Indeterminate/Bad accounts (application data)

Target	Frequency	Percent
Bad	2 358	28.88%
Good	5 154	63.12%
Indeterminate	654	8.01%
[redacted]		

From the above we can calculate the bad rate. The Bad rate is calculated as: Bad Rate = Bad / (Good + Bad) x 100. This yields an overall bad rate of 31.39% (2 358 / (2 358 + 5 154)).

Because of the filter applied (item 3.4.2.2) and the subsequent exclusion of 1 362 loans in the extraction of the data for the SBC development sample, there were less loans in the SBC sample as can be seen in table 3.3.

3 - Table 3.3 Distribution of Good/Indeterminate/Bad accounts (SBC data)

Target	Frequency	Percent
Bad	1 960	28.81%
Good	4 300	63.20%
Indeterminate	544	8.00%
[redacted]		

From the above the bad rate for the SBC sample is calculated as 1 960 / (1 960 + 4 300) = 31.30%.

3.6.2. Approval rate definition

The sample of loans analysed contained 8 166 loans, but these represent only the successful applicants. During the window period The Lender also received loan applications that were declined. In order to get a complete picture these declined applications also has to be reviewed. In the window period a total of 16 262 applicants were declined by The Lender which is 66.57% of the total applicants. The reasons for these declines were:

- Operational declines (10.16%) which are errors such as:
    - System error.
    - Unable to connect to database.
    - Error retrieving details to validate.
- Declines due to risk (88.23%) which are due to business rules on:
    - Number of judgements
    - Administration orders.

The remaining declines (1.61%) did not contain a reason for the decline.

3.7. The analysis of the characteristics

Every characteristic was analysed in two parts: the first part of the analysis was in terms of the calculated good vs. bad definition and the second part of the analysis was done in terms of approved vs. declined loans. The good/bad analysis proved a useful indicator for all of the characteristics analysed while the approved/declined analysis was only useful for some of the characteristics.

3.7.1. Good/bad accounts

The characteristics of the development data were analysed with respect to:

- The size of the specified values
- The percentage of good accounts
- The percentage of bad accounts
- The percentage of indeterminate accounts
- The development size
- The bad rates
- The relative bad rate
- The weight of evidence

3.7.1.1. Definitions for good/bad analysis

The following definitions apply to the good/bad analysis tables contained in the rest of this chapter:

- Bad Rate = Bad / (Good + Bad) x 100
- Relative Bad Rate = Bad Rate / Average Bad Rate
- % Good = Good / Total Good x 100
- % Bad = Bad /Total Bad x 100
- Weight of Evidence = *ln*(%Good / % Bad). A negative weight of evidence value constitutes high risk and a positive weight of evidence constitutes low risk. The higher the negative value, the higher the risk. The higher the positive value, the lower the risk.

3.7.1.2. Description of table headings (Good/Bad)

The following is a description of meanings of the good/bad table headings found in the rest of this chapter:

- **G:** the number of good accounts
- **B:** the number of bad accounts
- **I:** the number of indeterminate accounts
- **Total:** the sum of the good, bad and indeterminate accounts
- **Size:** the percentage of each attribute's contribution to the total
- **BR:** bad rate - the number of bad accounts divided by the sum of good and bad accounts
- **Relative BR:** the bad rate divided by the average bad rate
- **%G:** number of good accounts divided by the total number of good accounts x 100
- **%B:** number of bad accounts divided by the total number of bad accounts x 100
- **WOE:** (Weight of Evidence) natural logarithm of the percentage of good accounts divided by the percentage of bad accounts

3.7.2. Approval rate (accept/reject accounts)

The characteristics of the recent accept/reject data were analysed with respect to:

- The size of the specific values
- The approval rate (AR)
- The relative approval rate
- The percentage of approved accounts
- The percentage of reject accounts
- The weight of evidence

3.7.2.1. Definitions for approval rate (accept/reject)

The following definitions apply to the accept/reject analysis tables contained in the rest of this chapter:

- Approval Rate = Accepts / (Accepts + Rejects) x 100
- Relative Approval Rate = Approval Rate / Average Approval Rate
- % Accepts = Accepts / Total Accepts x 100
- % Rejects = Rejects / Total Rejects x 100
- Weight of evidence = *ln*(%Accepts / % Rejects) - the weight of evidence is interpreted as follows: a higher negative value means a lower approval rate and a higher positive value means a higher approval rate.

3.7.2.2. Description of table headings (accept/reject)

The following is a description of meanings of the accept/reject table headings found in the rest of this chapter:

- **A:** the number of accept accounts
- **R:** the number of reject accounts
- **Total:** the sum of the accept + reject accounts
- **Size:** the percentage of each attribute's contribution to the total
- **AR:** approval rate - the number of accept accounts divided by accept and reject accounts x 100
- **Relative AR:** the approval rate divided by the average approval rate

- **%A:** number of accounts divided by the total accept accounts x 100
- **%R:** number of reject accounts divided by the total reject accounts x 100
- **WOE:** (Weight of Evidence) natural logarithm of the percentage accepted accounts divided by the percentage rejected accounts.

3.8. Characteristics chosen to be used as scorecard variables

The choice of which characteristics to use in the scorecard was done by applying logistic regression. The logistic regression modelling is performed by way of a statistical software package. It entails loading the whole pool of variables into the statistical analysis program which then uses an algorithm to select the subset of characteristics that yield the best predictive result. The following characteristics were selected.

3.8.1. Application characteristics

The following application characteristics were the most significant in the modelling process and were used in the development of the application scorecard:

- Loan reason
- Age
- Bank name
- Bank account type
- Years at work
- Residential postal code (the residential postal codes were clustered into six groups based on relative income of the residents in the area; the development of this information is proprietary and can not be disclosed).

3.8.2. SBC characteristics

The following SBC characteristics were the most significant in the modelling process and were used in the development of the SBC scorecard.

- Number of trades opened in the last 24 months
- Number of trades 3 months or past due
- Number of enquiries in the last 24 months

- Utilisation of open trades
- Ratio of current satisfactory trades to open trades
- Age of oldest trade
- Number of defaults in the last 12 months
- Number of judgements in the last 24 months
- Number of satisfactory other trades
- Number of active revolving trades

3.8.3. Explanation for the negative values of attributes in the SBC

The following codes were used for some of the SBC attributes:

- -1 = Consumer has no trades on file.
- -2 = Consumer has no trades of this type on file.
- -3 = Consumer has no delinquency of this type on file.
- -4 = Value cannot be calculated.
- -5 = Consumer has no open trades on file.

3.9. The results of the application characteristics measured by bad rate

The application characteristics were first analysed in terms of bad rate. Only the results of the application characteristics that were included in the scorecard are contained in the tables that follow. Each characteristic will be introduced with a short description. The results of each table are also depicted in a graph.

3.9.1. Loan reason

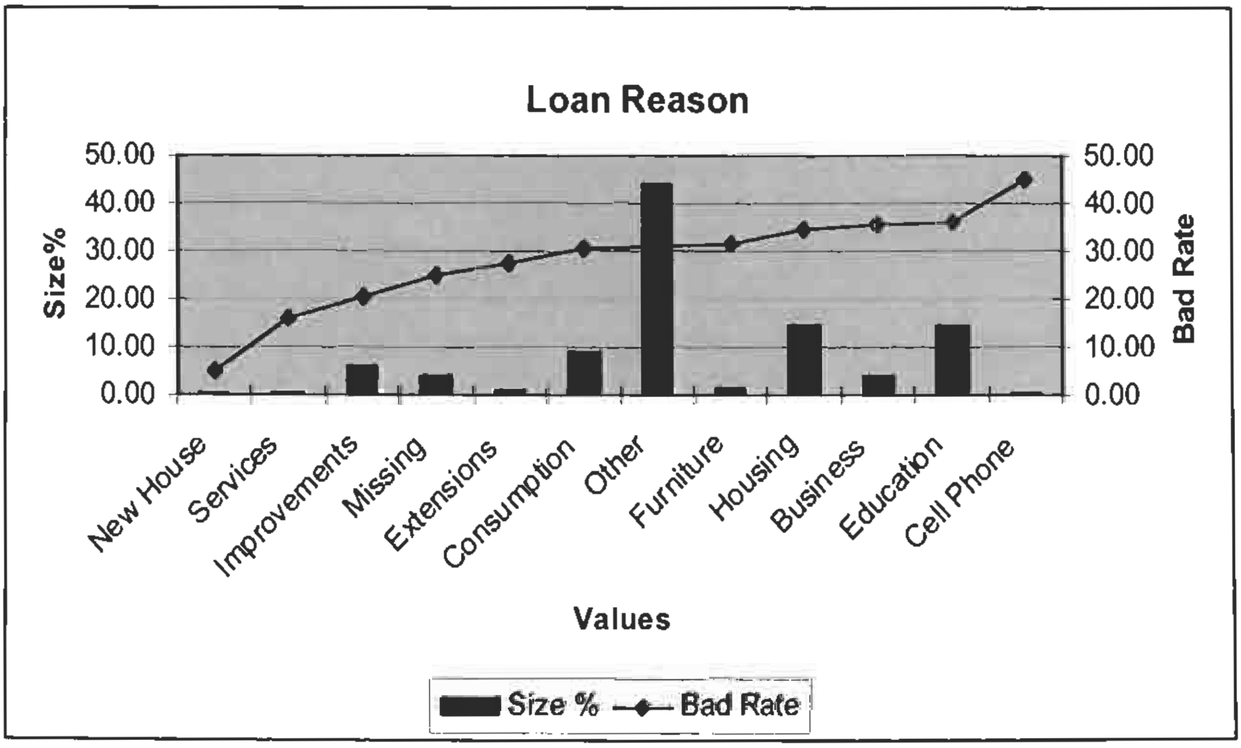
Each loan application had a category where the client was asked to state the reason for requesting the loan; these were standardised by way of tick boxes. In Table 3.4 the loan reasons were listed in an incremental fashion using the bad rate as denominator.

4 - Table 3.4: Loan Reason by Target

	Good_Bad_Inf				Size %	Bad rate	Relative	G %	B %	I %	WOE
Loan Reason	Bad	Good	Indet	Total			Bad Rate				
New House	2	37	2	41	0.50	5.13	0.16	0.7	0.1	0.3	2.14
Services	4	21	3	28	0.34	16.00	0.51	0.4	0.2	0.5	0.88
Improvements	94	363	29	486	5.95	20.57	0.66	7.0	4.0	4.4	0.57
Missing	79	238	21	338	4.14	24.92	0.79	4.6	3.4	3.2	0.32
Extensions	21	55	8	84	1.03	27.63	0.88	1.1	0.9	1.2	0.18
Consumption	207	474	47	728	8.92	30.40	0.97	9.2	8.8	7.2	0.05
Other	1030	2280	288	3598	44.06	31.12	0.99	44.2	43.7	44.0	0.01
Furniture	36	79	11	126	1.54	31.30	1.00	1.5	1.5	1.7	0.00
Housing	380	714	102	1196	14.65	34.73	1.11	13.9	16.1	15.6	-0.15
Business	108	195	27	330	4.04	35.64	1.14	3.8	4.6	4.1	-0.19
Education	388	687	113	1188	14.55	36.09	1.15	13.3	16.5	17.3	-0.21
Cell Phone	9	11	3	23	0.28	45.00	1.43	0.2	0.4	0.5	-0.58
Total	**2358**	**5154**	**654**	**8166**	**100.00**	**31.39**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

When the above results are expressed graphically (Graph 3.1) it is clear that loan reason has a differential correlation with bad rate.

1 – Graph 3.1: Loan Reason



3.9.2. Age

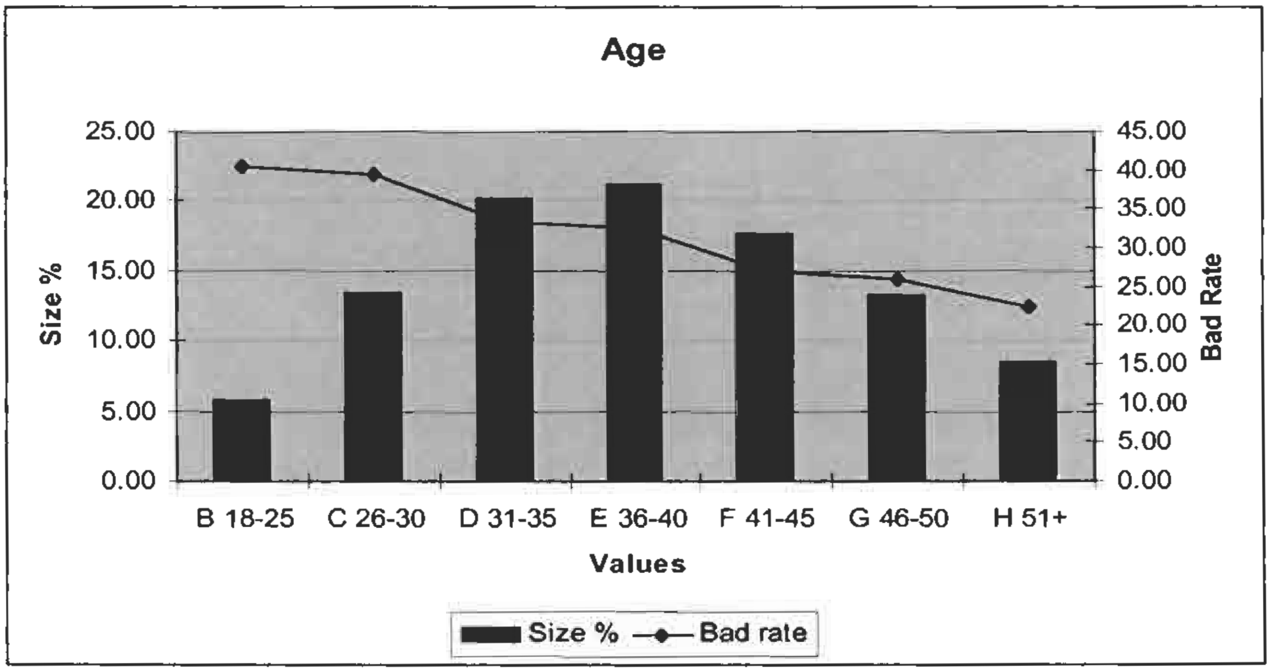
The business rules of The Lender only allowed loans to persons between 21 and 58 years of age. The ages were grouped together as depicted in Table 3.6.

5 - Table 3.5: Age

Age	Good_Bad_Int				Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet.	Total							
B 18-25	178	262	38	478	5.85	40.45	1.29	5.1	7.5	5.8	-0.40
C 26-30	398	613	88	1099	13.46	39.37	1.25	11.9	16.9	13.5	-0.35
D 31-35	510	1018	119	1647	20.17	33.38	1.06	19.8	21.6	18.2	-0.09
E 36-40	517	1068	143	1728	21.16	32.62	1.04	20.7	21.9	21.9	-0.06
F 41-45	353	958	131	1442	17.66	26.93	0.86	18.6	15.0	20.0	0.22
G 46-50	258	737	90	1085	13.29	25.93	0.83	14.3	10.9	13.8	0.27
H 51+	144	498	45	687	8.41	22.43	0.71	9.7	6.1	6.9	0.46
Total	**2358**	**5154**	**654**	**8166**	**100.00**	**31.39**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

There is a clear correlation between age and bad rate (Graph 3.2); older borrowers have lower bad rates.

2 - Graph 3.2: Age



3.9.3. Bank name

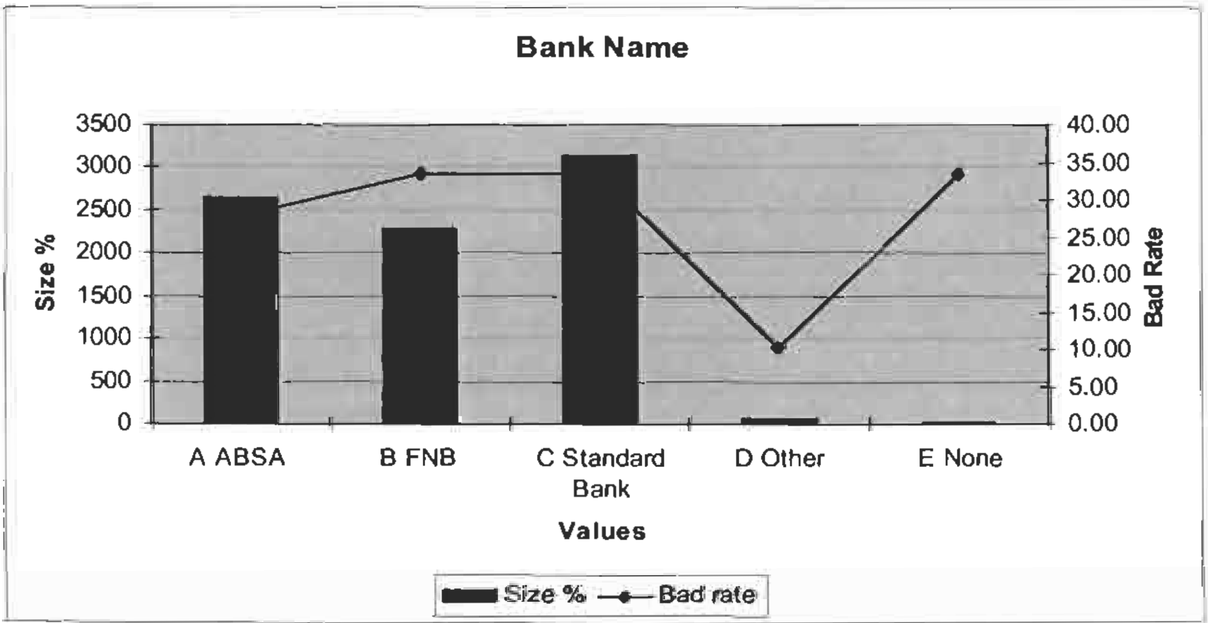
Due to access to specific payment mechanisms available to The Lender, the business rules only allowed loans to be given to account holders of three of the commercial banks. The incidence of other banks in the sample below is due to borrowers changing banks after the loans were granted.

6 - Table 3.6: Bank Name by Target

Bank Name	Good_Bad_Int			Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet								
A ABSA	685	1770	200	2655	32.51	27.90	0.89	34.3	29.1	30.6	0.17
B FNB	700	1401	181	2282	27.95	33.32	1.06	27.2	29.7	27.7	-0.09
C Standard Bank	961	1911	265	3137	38.42	33.46	1.07	37.1	40.8	40.5	-0.09
D Other	7	62	3	72	0.88	10.14	0.32	1.2	0.3	0.5	1.40
E None	5	10	5	20	0.24	33.33	1.06	0.2	0.2	0.8	-0.09
Total	**2358**	**5154**	**654**	**8166**	**100.00**	**31.39**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

As seen in Graph 3.3, there is a differential correlation between bad rate and the borrower's bank. It has to be stressed at this point that the result of this characteristic is a result of specific payment mechanisms available to The Lender at each of the three banks. The Lender did not have similar mechanisms at other banks and therefore declined borrowers that did not bank at these banks, hence the low number of other banks (category D). The incidence of borrowers in the other category is due to natural migration of borrowers to other banks after the loan was granted.

3 - Graph 3.3: Bank name



3.9.4. Account type

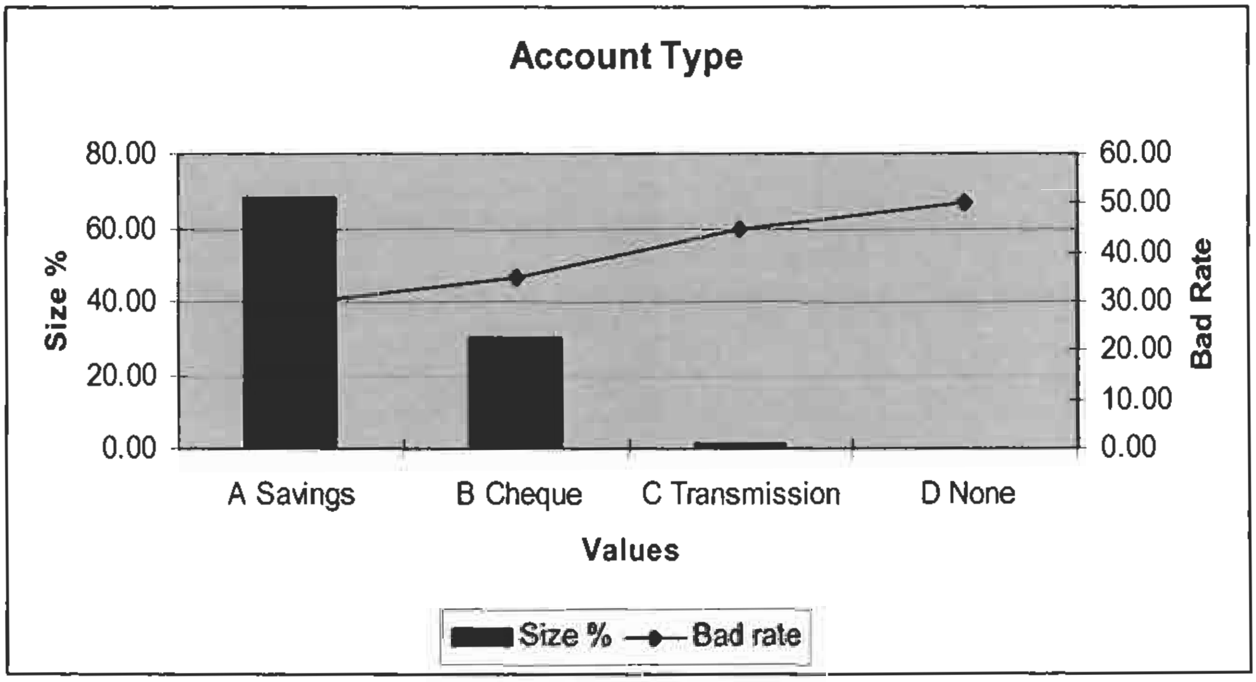
The account type is the type of bank account into which the borrower's remuneration is deposited and the instalments are collected by way of a debit order.

7 - Table 3.7: Account type by target

Account Type	Good_Bad_Inf Bad	Good	Indet.	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
A Savings	1522	3628	440	5590	68.45	29.55	0.94	70.4	64.5	67.3	0.09
B Cheque	784	1462	198	2444	29.93	34.91	1.11	28.4	33.2	30.3	-0.16
C Transmission	51	63	15	129	1.58	44.74	1.43	1.2	2.2	2.3	-0.57
D None	1	1	1	3	0.04	50.00	1.59	0.0	0.0	0.2	-0.78
Total	**2358**	**5154**	**654**	**8166**	**100.00**	**31.39**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

The differential correlation between the various bank account types and bad rate can be seen in Graph 3.4.

4 - Graph 3.4: Account type



3.9.5. Years at work

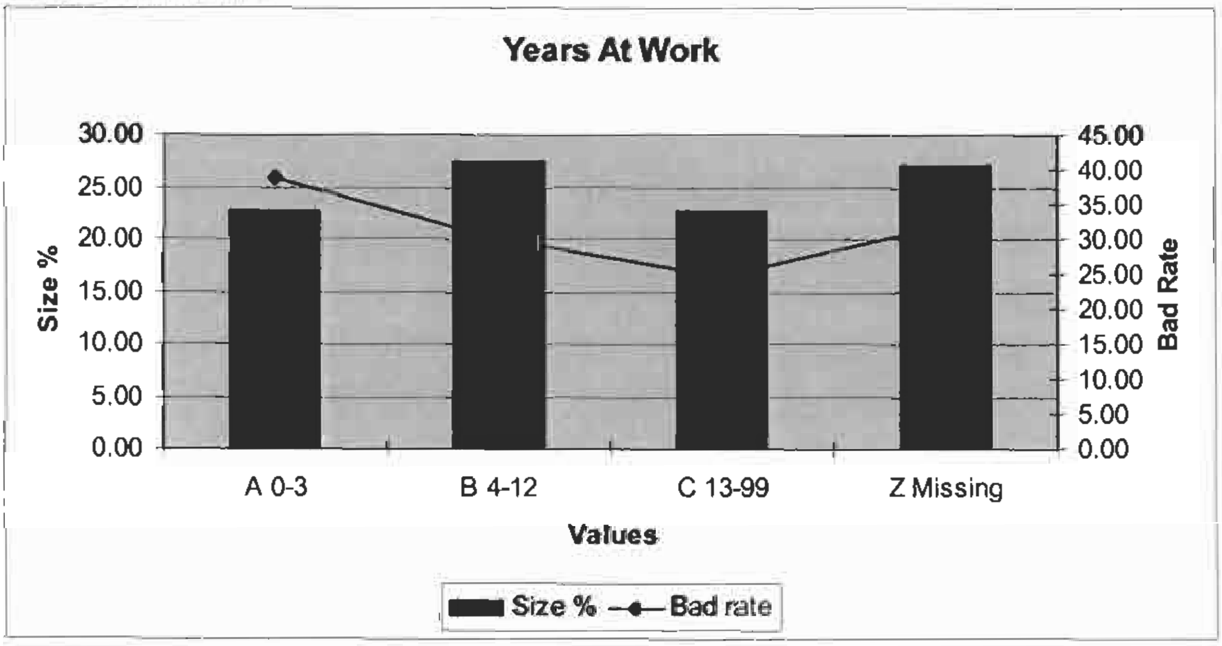
This is the length of time that the client has been employed at his/her current work place. The possibilities were grouped into three categories.

8 - Table 3.8: Years at work

	Good_Bad_Int										
Years at Work	Bad	Good	Indet.	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
A 0-3	668	1049	141	1858	22.75	38.91	1.24	20.4	28.3	21.6	-0.33
B 4-12	616	1437	196	2249	27.54	30.00	0.96	27.9	26.1	30.0	0.07
C 13-99	422	1277	156	1855	22.72	24.84	0.79	24.8	17.9	23.9	0.33
Z Missing	652	1391	161	2204	26.99	31.91	1.02	27.0	27.7	24.6	-0.02
Total	2358	5154	654	8166	100.00	31.39	1.00	100.0	100.0	100.0	0.00

It is clear from Graph 3.5 that there is a negative correlation between the length of employment and bad rate. Expressed differently one could say the longer a borrower has been working at one employer the better they are at repaying their loan.

5 - Graph 3.5: Years at work



3.9.6. Residential Postal Code

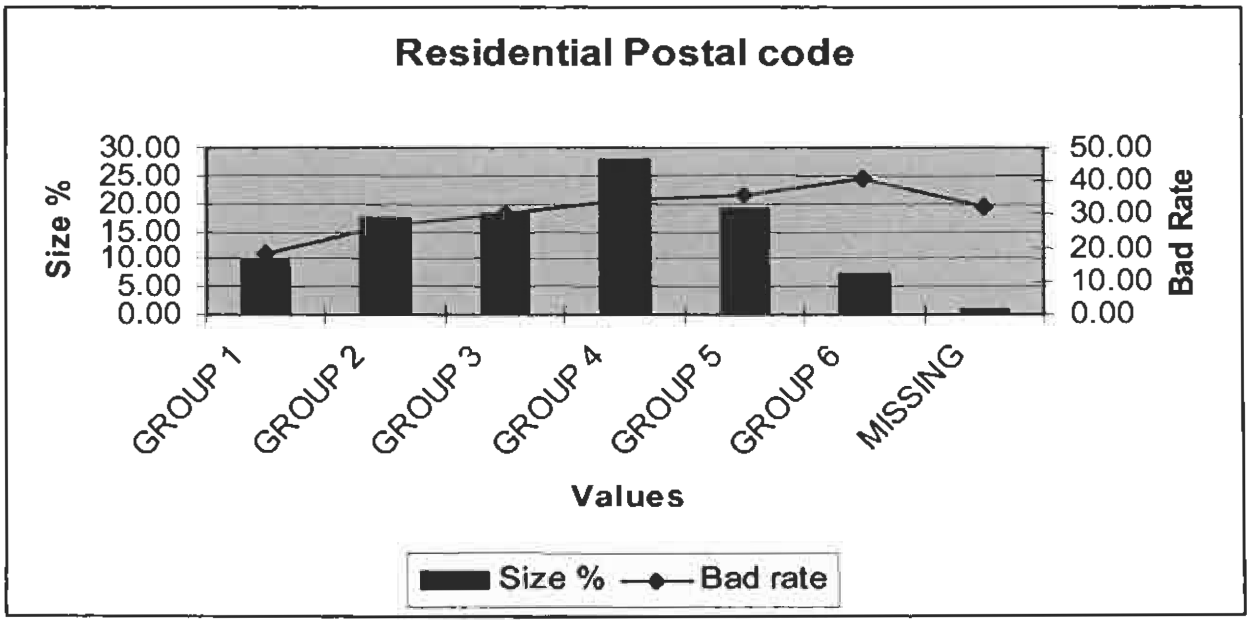
Postal codes were grouped together based on demographic information categorising areas according to affluence. Group 1 consists of areas of high mean income, decreasing to Group 6 which consists of areas of low mean income.

9 - Table 3.9: Residential Postal Code

Residential Postal Code	Good_Bad_Int			Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet								
GROUP 1	142	619	47	808	9.89	18.66	0.59	12.0	6.0	7.2	0.69
GROUP 2	353	983	92	1428	17.49	26.42	0.84	19.1	15.0	14.1	0.24
GROUP 3	406	942	132	1480	18.12	30.12	0.96	18.3	17.2	20.2	0.06
GROUP 4	716	1364	194	2274	27.85	34.42	1.10	26.5	30.4	29.7	-0.14
GROUP 5	508	896	132	1536	18.81	36.18	1.15	17.4	21.5	20.2	-0.21
GROUP 6	214	310	54	578	7.08	40.84	1.30	6.0	9.1	8.3	-0.41
MISSING	19	40	3	62	0.76	32.20	1.03	0.8	0.8	0.5	-0.04
Total	2358	5154	654	8166	100.00	31.39	1.00	100.0	100.0	100.0	0.00

There is a correlation between postal code group and bad rate. The more affluent areas have a lower bad rate than the less affluent ones. In simple terms this means that people with a postal code in a more affluent group were found to be better payers than those in the least affluent postal code group.

6 - Graph 3.6: Residential postal code



Each of the application characteristics had a distinguishing result in terms of the bad rate.

3.10. The results of the application by approval rate

The application characteristics were also analysed in term of acceptance rate and the only characteristic that showed a significant correlation was age.

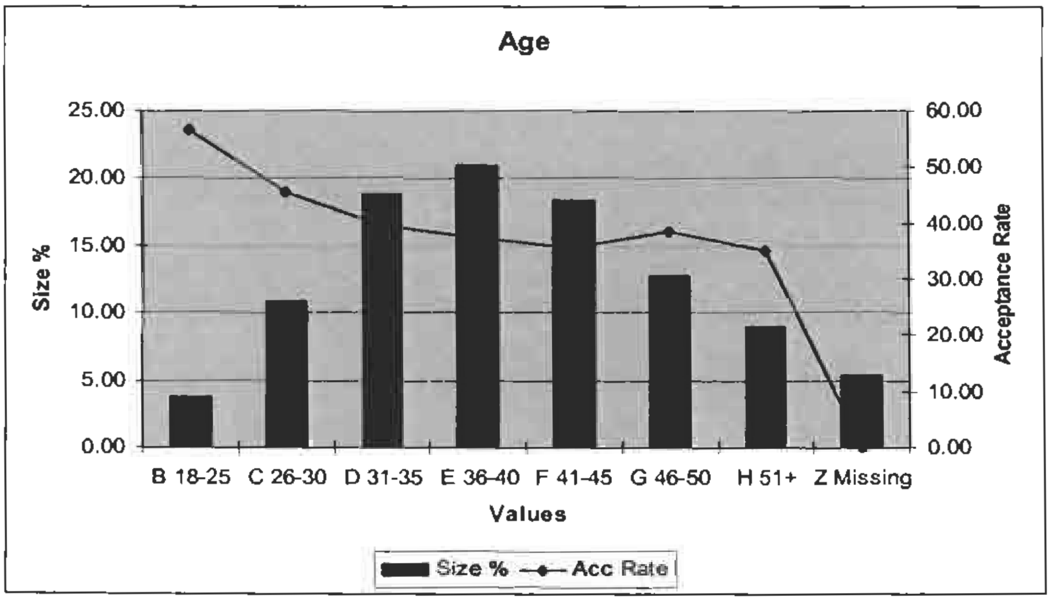
3.10.1. Age

10 - Table 3.10: Age by Accept/Reject flag

Age	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
B 18-25	490	375	865	3.80	56.65	5.8	0.0	5.40
C 26-30	1130	1351	2481	10.89	45.55	13.4	0.1	4.96
D 31-35	1696	2588	4284	18.81	39.59	20.1	0.2	4.71
E 36-40	1784	2992	4776	20.97	37.35	21.2	0.2	4.62
F 41-45	1499	2699	4198	18.43	35.71	17.8	0.2	4.55
G 46-50	1113	1789	2902	12.74	38.35	13.2	0.1	4.66
H 51+	716	1324	2040	8.96	35.10	8.5	0.1	4.52
Z Missing	0	1230	1230	5.40	0.00	0.0	0.1	99.99
Total	**8428**	**14348**	**22776**	**100.00**	**37.00**	**100.0**	**1.0**	**4.61**

There is a negative correlation between the acceptance rate and the age of applicants as can be seen in Graph 3.7. This seems to be in contrast with the bad rate results which indicated that older borrowers have lower bad rates. A possible explanation for the discrepancy is that older applicants have a longer credit history, enabling The Lender to reject the more risky older applicants, resulting in a lower acceptance rate but yielding a better payment rate.

7 - Graph 3.7: Age



3.11. The results of the standard batch characteristics (SBC) measured by bad rate

The SBC development sample was analysed in exactly the same way as the previous characteristics and yielded the results that follow. A short description is given for each characteristic. Also see item 3.8.3 for the meaning of attributes with negative score values.

3.11.1. Number of trades opened in the last 12 months

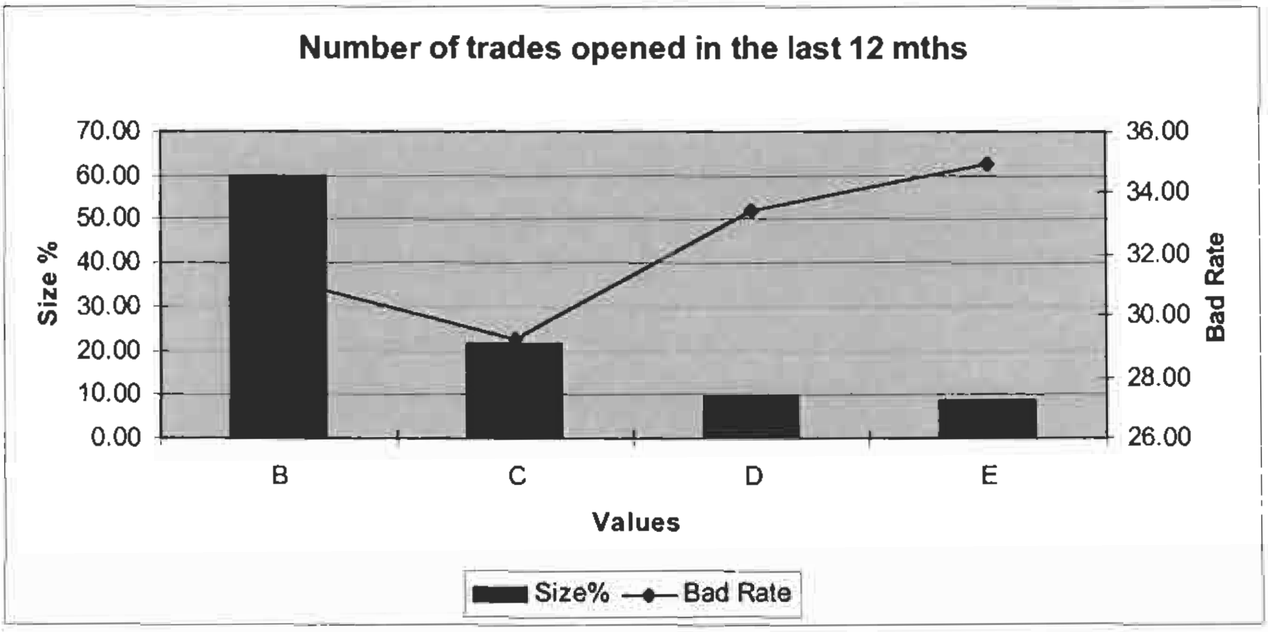
This is the number of other accounts opened or loans received by the borrower.

11 - Table 3.11: No. of trades opened in the last 12 months

No. of trades opened	Good_Bad_Ind				Size %	Bad rate	Relative	G %	B %	I %	WOE
In last 12 Mths	Bad	Good	Indet	Total			Bad Rate				
B_00	1161	2559	340	4060	59.67	31.21	1.00	59.5	59.2	62.5	0.00
C_01	404	979	103	1486	21.84	29.21	0.93	22.8	20.6	18.9	0.10
D_02	206	410	57	673	9.89	33.44	1.07	9.5	10.5	10.5	-0.10
E_03-HIGH	189	352	44	585	8.60	34.94	1.12	8.2	9.6	8.1	-0.16
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

There is a differential correlation between the number of trades that a borrower has opened in the last 12 months and bad rate.

8 - Graph 3.8: Number of open trades in the last 12 months



3.11.2. Number of trades 3 months or past due

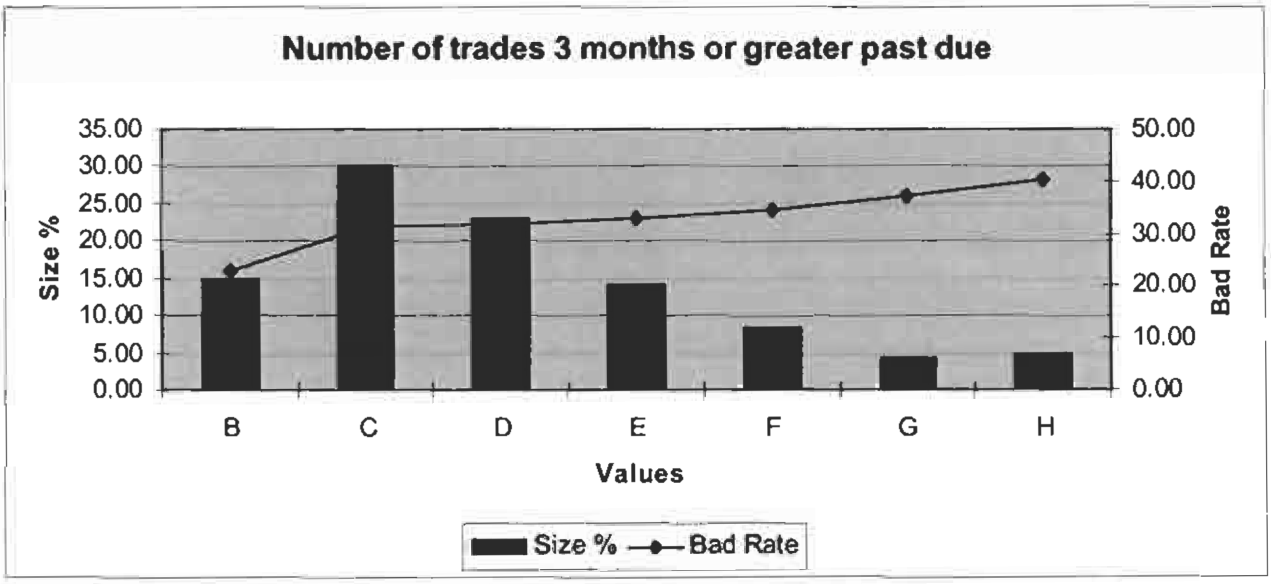
This is the number of accounts that have been in a state of arrears for three months or more at some stage in its life cycle.

12 - Table 3.12: Number of trades 3 months or more past due

No. of trades 3 mth or > PD	Good_Bad_Int Bad	Good	Indet.	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
B_00	221	749	54	1024	15.05	22.78	0.73	17.4	11.3	9.9	0.43
C_01	594	1301	157	2052	30.16	31.35	1.00	30.3	30.3	28.9	0.00
D_02	454	970	142	1566	23.02	31.88	1.02	22.6	23.2	26.1	-0.03
E_03	291	589	80	960	14.11	33.07	1.06	13.7	14.8	14.7	-0.08
F_04	180	344	51	575	8.45	34.35	1.10	8.0	9.2	9.4	-0.14
G_05	98	165	32	295	4.34	37.26	1.19	3.8	5.0	5.9	-0.26
H_06-HIGH	122	182	28	332	4.88	40.13	1.28	4.2	6.2	5.1	-0.39
Total	1960	4300	544	6804	100.00	31.31	1.00	100.0	100.0	100.0	0.00

There is a correlation between the number of trades more than three months in arrears and bad rate.

9 - Graph 3.9: Number of trades 3 months or more past due



3.11.3. Number of enquiries in the last 24 months

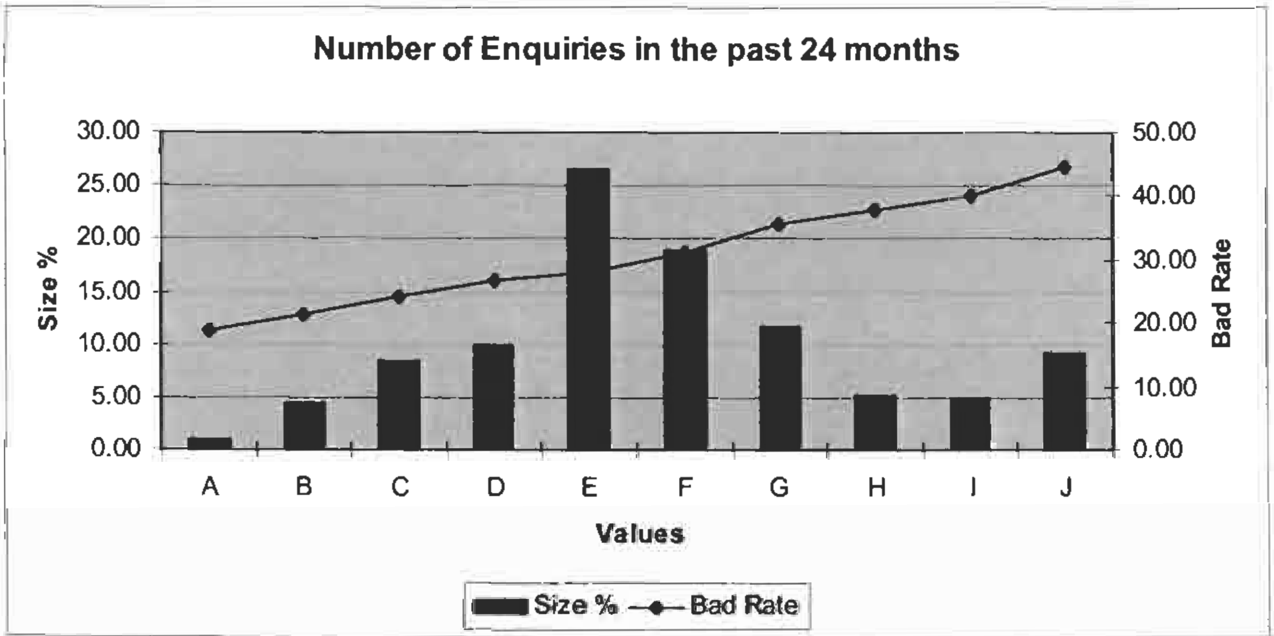
This is a count of the number of times lenders have accessed the bureau for a credit check on an applicant. A high count might indicate somebody who is very credit active and is over-extending himself. A high count with few approvals could indicate a borrower desperate for credit who cannot get any. The numbers of enquiries have been grouped together in ten categories (attributes) as can be seen in Table 3.13.

13 - Table 3.13: Number of Enquiries in the past 24 months

No. of enquiries in the past 24 mths	Good_Bad_Int				Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet.	Total							
A_-01	12	52	0	64	0.94	18.75	0.60	1.2	0.6	0.0	0.68
B_00	58	213	31	302	4.44	21.40	0.68	5.0	3.0	5.7	0.52
C_01	130	408	32	570	8.38	24.16	0.77	9.5	6.6	5.9	0.36
D_02	165	452	53	670	9.85	26.74	0.85	10.5	8.4	9.7	0.22
E_03-05	471	1204	132	1807	26.56	28.12	0.90	28.0	24.0	24.3	0.15
F_06-08	369	810	107	1286	18.90	31.30	1.00	18.8	18.8	19.7	0.00
G_09-11	257	462	71	790	11.61	35.74	1.14	10.7	13.1	13.1	-0.20
H_12-13	123	201	25	349	5.13	37.96	1.21	4.7	6.3	4.6	-0.29
I_14-16	123	184	35	342	5.03	40.07	1.28	4.3	6.3	6.4	-0.38
J_17-HIGH	252	314	58	624	9.17	44.52	1.42	7.3	12.9	10.7	-0.57
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

There is a strong positive correlation between the number of enquiries and the bad rate.

10 - Graph 3.10: Number of enquiries in the past 24 months



3.11.4. Utilisation of open trades

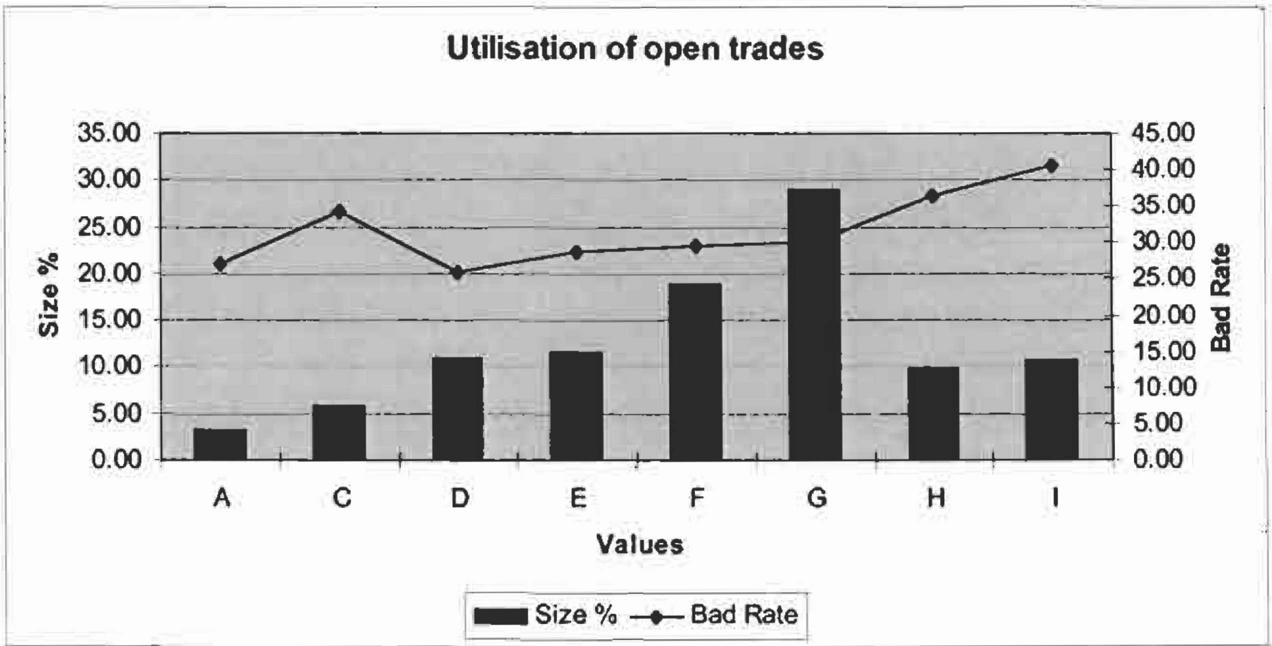
This is a measure of how often a borrower uses his/her revolving credit accounts (account with an open ended balance). Utilisation is an indication of how a borrower manages these accounts but does not take into consideration whether the accounts are used to their maximum limits or not. The number of open trades utilised were grouped together in 8 categories.

14 - Table 3.14: Utilisation of open trades

Utilisation of open Trades	Good_Bad_Int Bad	Good	Indet.	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
A_-4	55	148	11	214	3.15	27.09	0.87	3.4	2.8	2.0	0.20
C_00	122	233	37	392	5.76	34.37	1.10	5.4	6.2	6.8	-0.14
D_0.1-25.0	177	507	63	747	10.98	25.88	0.83	11.8	9.0	11.6	0.27
E_25.1-40.0	210	519	57	786	11.55	28.81	0.92	12.1	10.7	10.5	0.12
F_40.1-60.0	348	828	109	1285	18.89	29.59	0.95	19.3	17.8	20.0	0.08
G_60.1-90.0	551	1273	147	1971	28.97	30.21	0.96	29.6	28.1	27.0	0.05
H_90.1-100.0	228	399	50	677	9.95	36.36	1.16	9.3	11.6	9.2	-0.23
I_100.1-HIGH	269	393	70	732	10.76	40.63	1.30	9.1	13.7	12.9	-0.41
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

From category C and upwards there is a clear positive correlation with bad rate.

11 - Graph 3.11: Utilisation of open trades



3.11.5. Ratio of current satisfactory trades to open trades

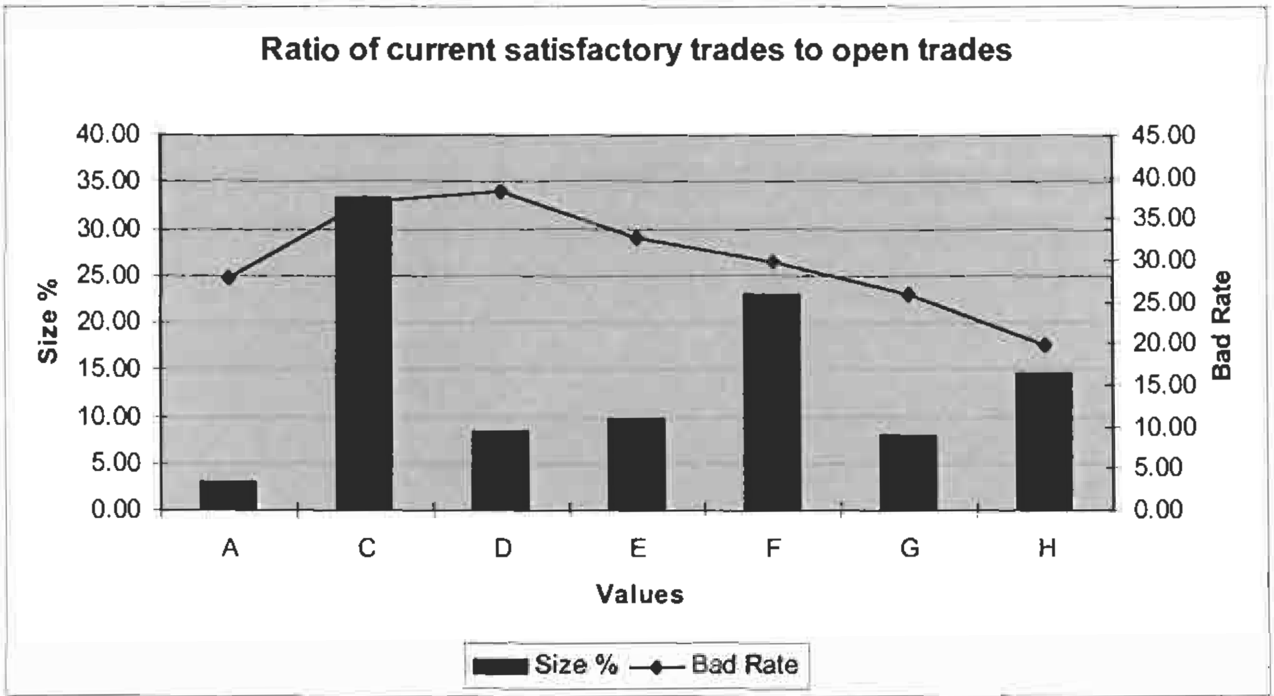
Current satisfactory trades are accounts that are current with regard to payment and which have a favourable debt status. The different values were grouped together in seven categories.

15 - Table 3.15: Ratio of current satisfactory trades to open trades

Ratio of curr. satisf. trades to open trades	Good_Bad_Int				Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet.	Total							
A_-4	53	138	11	202	2.97	27.75	0.89	3.2	2.7	2.0	0.17
C_0	766	1297	212	2275	33.44	37.13	1.19	30.2	39.1	39.0	-0.26
D_0.1-30.0	199	320	52	571	8.39	38.34	1.22	7.4	10.2	9.6	-0.31
E_30.1-40.0	198	408	51	657	9.66	32.67	1.04	9.5	10.1	9.4	-0.06
F_40.1-70.0	428	1011	123	1562	22.96	29.74	0.95	23.5	21.8	22.6	0.07
G_70.1-99.9	131	377	34	542	7.97	25.79	0.82	8.8	6.7	6.3	0.27
H_100	185	749	61	995	14.62	19.81	0.63	17.4	9.4	11.2	0.61
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

Categories A to D have a positive correlation with bad rate; thereafter it becomes negative.

12 - Graph 3.12: Ratio of current satisfactory trades to open trades



3.11.6. Age of oldest trade

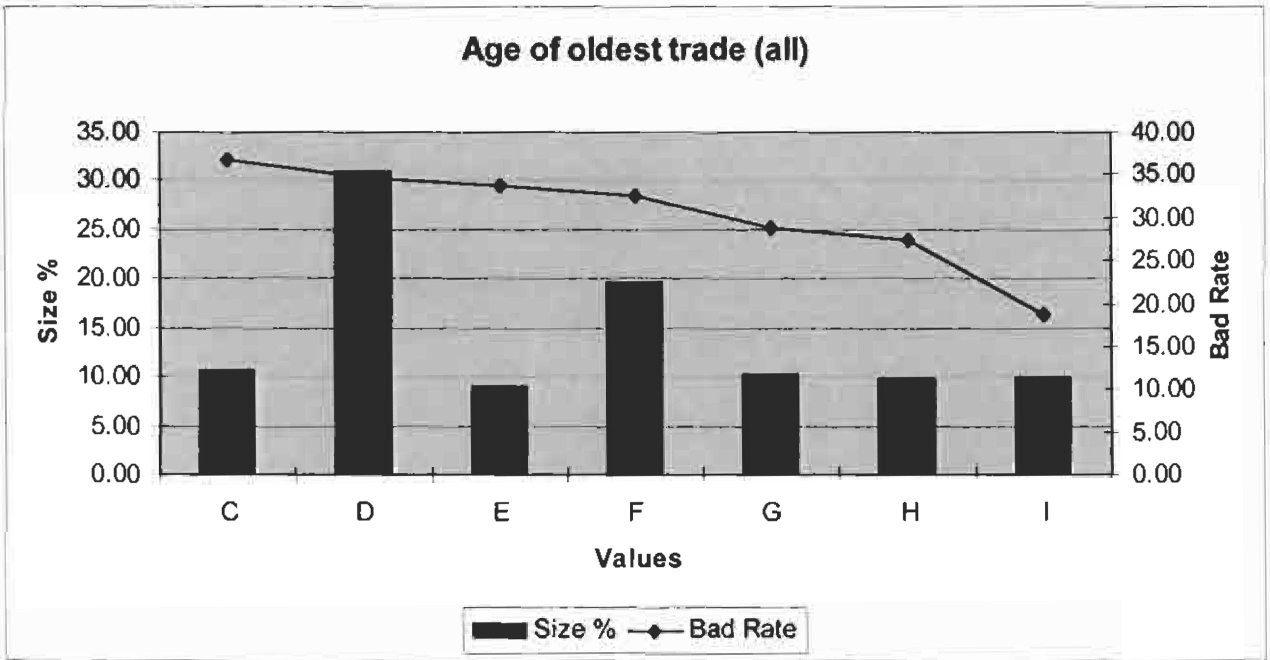
This is a measure of how long a borrower has been credit active (measured in months).

16 - Table 3.16: Age of oldest trade

Age of oldest trade (all)	Good_Bad_Int Bad	Good	Indet.	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
C_00-21	244	420	54	718	10.55	36.75	1.17	9.8	12.4	9.9	-0.24
D_22-48	661	1253	184	2098	30.83	34.54	1.10	29.1	33.7	33.8	-0.15
E_49-57	190	376	50	616	9.05	33.57	1.07	8.7	9.7	9.2	-0.10
F_58-83	393	820	121	1334	19.61	32.40	1.03	19.1	20.1	22.2	-0.05
G_84-108	184	458	56	698	10.26	28.66	0.92	10.7	9.4	10.3	0.13
H_109-139	168	448	47	663	9.74	27.27	0.87	10.4	8.6	8.6	0.20
I_140-HIGH	120	525	32	677	9.95	18.60	0.59	12.2	6.1	5.9	0.69
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

There is a definite negative correlation between the age of the oldest trade and bad rate.

13 - Graph 3.13: Age of oldest trade



3.11.7. Number of defaults in the last 12 months

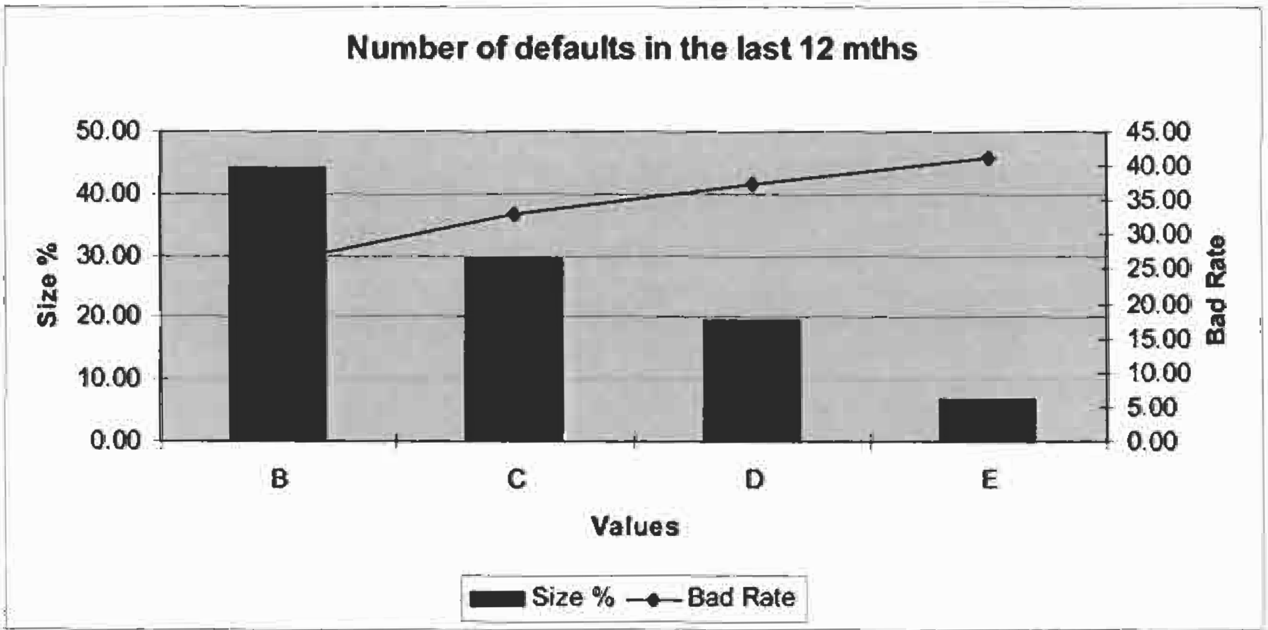
A default is when a lender "black lists" a borrower as a bad payer. A high number of defaults would indicate that a borrower is in financial distress.

17 - Table 3.17: Number of defaults in the last 12 months

No. of defaults in the last 12 Mths	Good_Bad_Int										
	Bad	Good	Indet	Total	Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
B_-02	732	2075	205	3012	44.27	26.08	0.83	48.3	37.3	37.7	0.26
C_00	599	1219	184	2002	29.42	32.95	1.05	28.3	30.6	33.8	-0.08
D_01	457	761	112	1330	19.55	37.52	1.20	17.7	23.3	20.6	-0.28
E_02-HIGH	172	245	43	460	6.76	41.25	1.32	5.7	8.8	7.9	-0.43
Total	1960	4300	544	6804	100.00	31.31	1.00	100.0	100.0	100.0	0.00

There is a strong positive correlation between bad rate and the number of defaults.

14 - Graph 3.14: Number of defaults in the last 12 months



3.11.8. Number of judgements in the last 24 months

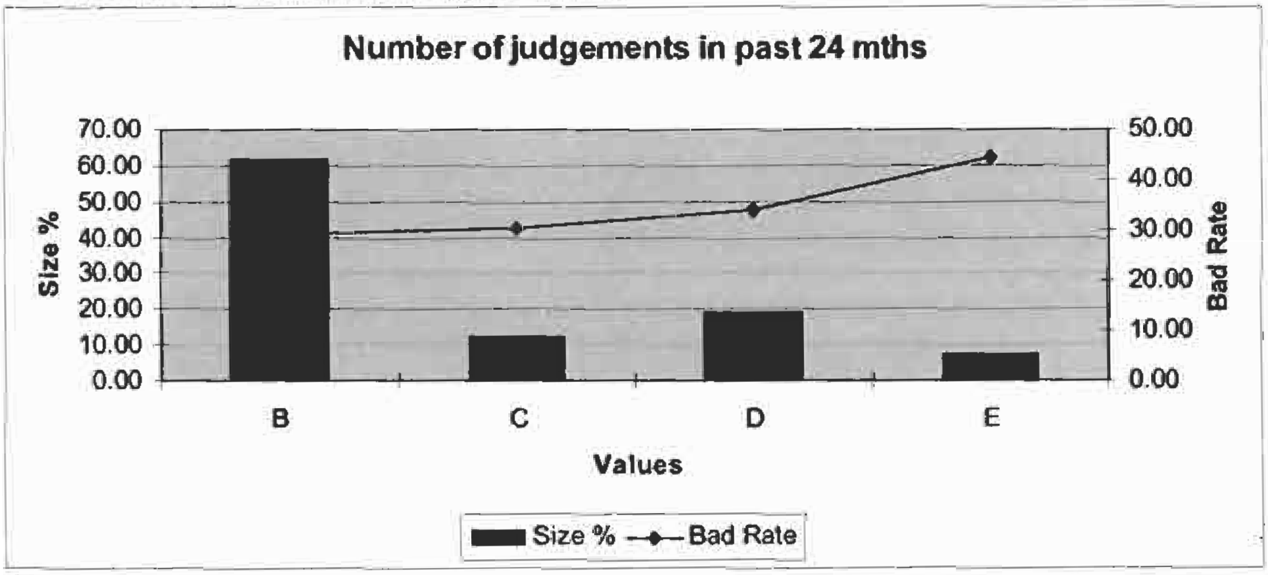
A judgement is when a lender obtains a legal order from the court to attach the assets of a borrower who has not honoured his/her debt commitments.

18 - Table 3.18: Number. of judgements in the past 24 mths

No. of judgements in the past 24 mths	Good_Bad_Int				Size %	Bad rate	Relative	G %	B %	I %	WOE
	Bad	Good	Indet.	Total			Bad Rate				
B_-02	1141	2764	303	4208	61.85	29.22	0.93	64.3	58.2	55.7	0.10
C_00	236	536	63	835	12.27	30.57	0.98	12.5	12.0	11.6	0.03
D_01	396	764	123	1283	18.86	34.14	1.09	17.8	20.2	22.6	-0.13
E_02-HIGH	187	236	55	478	7.03	44.21	1.41	5.5	9.5	10.1	-0.55
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

There is a clear correlation between the number of judgements and the bad rate.

15 - Graph 3.15: Number of judgements in the past 12 months



3.11.9. Number of satisfactory other trades

These trades are not in default i.e. payments are up to date.

19 - Table 3.19: Number of satisfactory other trades

No. of satisfactory other trades	Good_Bad_Int				Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet.	Total							
A_-02	1210	2682	355	4247	62.42	31.09	0.99	62.4	61.7	65.3	0.01
C_00	341	499	88	928	13.64	40.60	1.30	11.6	17.4	16.2	-0.40
D_01	298	747	70	1115	16.39	28.52	0.91	17.4	15.2	12.9	0.13
E_02-HIGH	111	372	31	514	7.55	22.98	0.73	8.7	5.7	5.7	0.42
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

After an initial positive correlation for categories A and C with bad rate, the correlation becomes negative.

16 - Graph 3.16: Number of satisfactory other trades

3.11.10. Number of active revolving trades

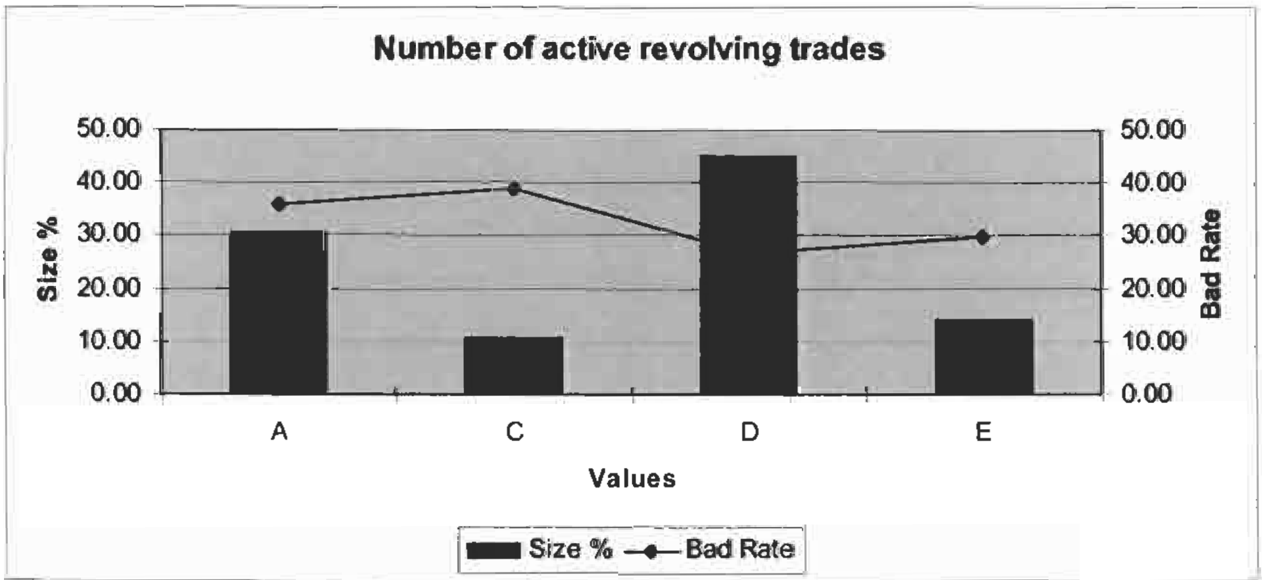
A revolving trade is an account where a borrower has a credit limit and the loan repayment can change from month to month depending on the level of usage. An example of a revolving account would be an account at a clothing store.

20 - Table 3.20: Number of active revolving trades

No. of active revolving trades	Good_Bad_Int				Size %	Bad rate	Relative Bad Rate	G %	B %	I %	WOE
	Bad	Good	Indet.	Total							
A_-02	682	1209	181	2072	30.45	36.07	1.15	28.1	34.8	33.3	-0.21
C_00	256	402	63	721	10.60	38.91	1.24	9.3	13.1	11.6	-0.33
D_01-02	760	2068	232	3060	44.97	26.87	0.86	48.1	38.8	42.6	0.22
E_03-HIGH	262	621	68	951	13.98	29.67	0.95	14.4	13.4	12.5	0.08
Total	**1960**	**4300**	**544**	**6804**	**100.00**	**31.31**	**1.00**	**100.0**	**100.0**	**100.0**	**0.00**

The graph indicates that borrowers with no revolving trades have a high bad rate, possibly because they did not qualify for revolving credit. There is a differential correlation between higher numbers of active revolving trades and bad rate.

17 - Graph 3.17: Number of active revolving trades



3.12. The results of the standard batch characteristics (SBC) measured by approval rate

All the characteristics of the SBC development sample showed a statistical correlation with regard to acceptance rate. Refer to section 3.11 for the definitions of the characteristics.

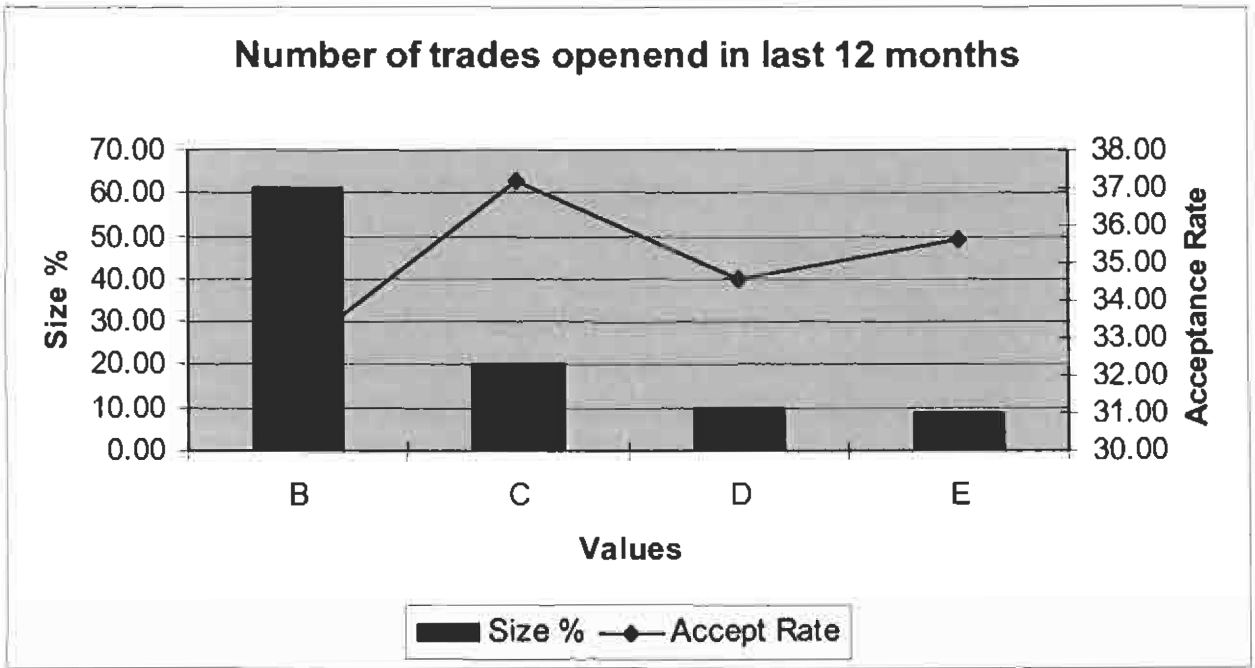
3.12.1. Number of trades opened in the last 12 months

21 - Table 3.21: Number of trades opened in last 12 Months

No. of trades opened in last 12 Mths	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
B_00	3529	7276	10805	61.28	32.66	58.8	62.5	-0.06
C_01	1327	2240	3567	20.23	37.20	22.1	19.3	0.14
D_02	600	1137	1737	9.85	34.54	10.0	9.8	0.02
E_03-HIGH	542	980	1522	8.63	35.61	9.0	8.4	0.07
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a differential correlation between the number of trades opened in the last twelve months and bad rate as seen in Graph 3.18.

18 - Graph 3.18: Number of trades opened in the last 12 months



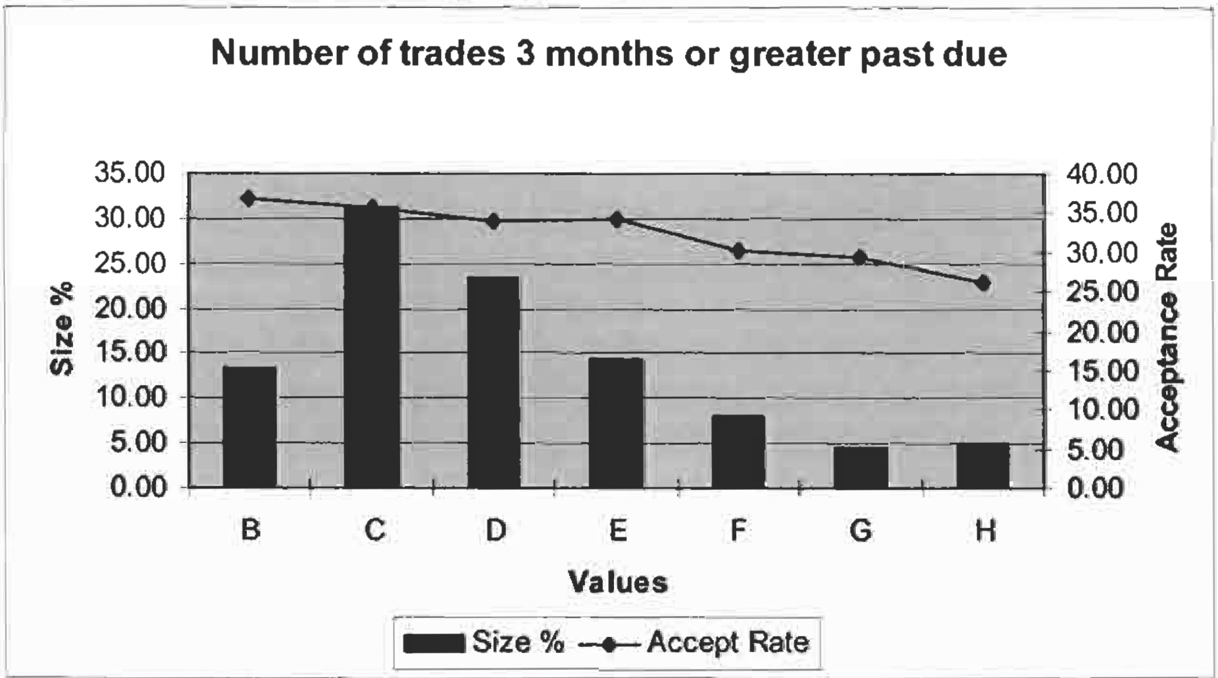
3.12.2. Number of trades 3 months or greater past due

22 - Table 3.22: Number of trades 3 months or greater past due

No. of trades 3 mth or > PD	AR_Flag Accept	Reject	Total	Size %	Acc Rate	Accept %	Reject %	WOE
B_00	867	1483	2350	13.33	36.89	14.5	12.7	0.13
C_01	1956	3542	5498	31.18	35.58	32.6	30.4	0.07
D_02	1412	2735	4147	23.52	34.05	23.5	23.5	0.00
E_03	864	1655	2519	14.29	34.30	14.4	14.2	0.01
F_04	432	999	1431	8.12	30.19	7.2	8.6	-0.18
G_05	234	561	795	4.51	29.43	3.9	4.8	-0.21
H_06-HIGH	233	658	891	5.05	26.15	3.9	5.7	-0.38
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a negative correlation between acceptance rate and this characteristic.

19 - Graph 3.19: Number of trades 3 months or greater past due



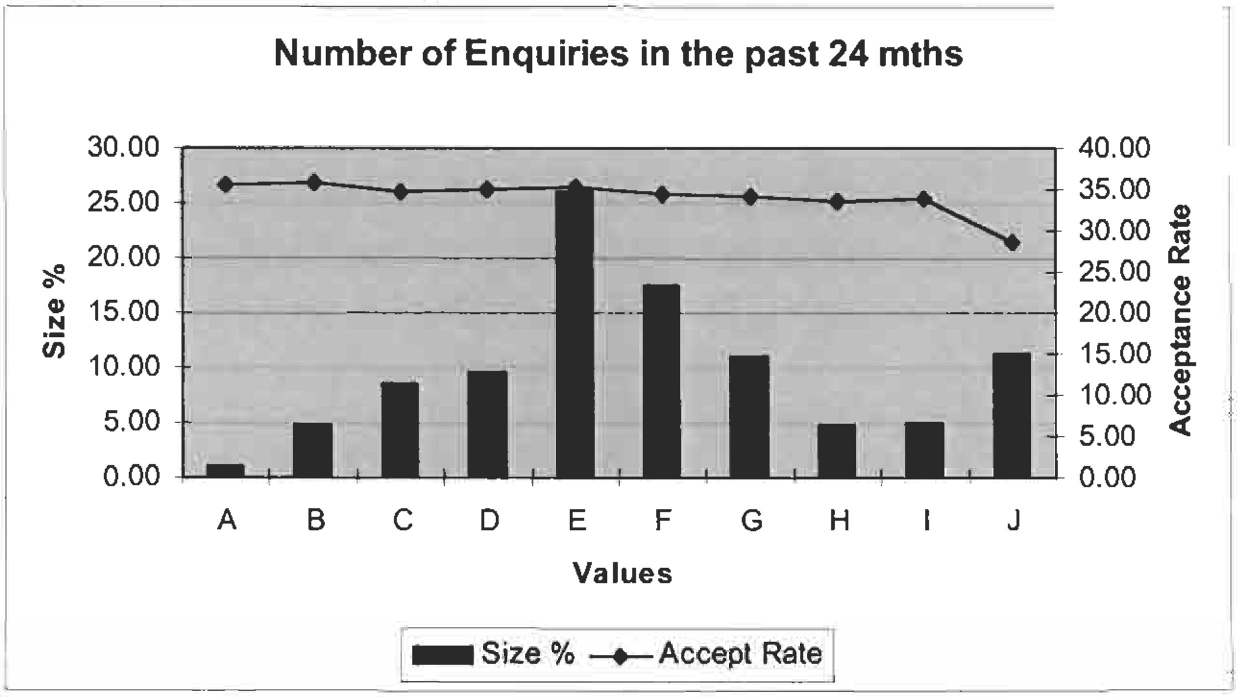
3.12.3. Number of enquiries in the last 24 months

23 - Table 3.23: Number. of Enquiries in the past 24 months

No. of enquiries in the past 24 mths	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
A_-01	72	130	202	1.15	35.64	1.2	1.1	0.07
B_00	307	552	859	4.87	35.74	5.1	4.7	0.08
C_01	524	989	1513	8.58	34.63	8.7	8.5	0.03
D_02	597	1108	1705	9.67	35.01	10.0	9.5	0.04
E_03-05	1613	2966	4579	25.97	35.23	26.9	25.5	0.05
F_06-08	1063	2032	3095	17.55	34.35	17.7	17.5	0.01
G_09-11	664	1272	1936	10.98	34.30	11.1	10.9	0.01
H_12-13	286	568	854	4.84	33.49	4.8	4.9	-0.02
I_14-16	301	588	889	5.04	33.86	5.0	5.1	-0.01
J_17-HIGH	571	1428	1999	11.34	28.56	9.5	12.3	-0.25
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

Graph 3.20 shows a negative (though weak) correlation between acceptance rate and number of enquiries.

20 - Graph 3.20: Number of enquiries in the past 24 months



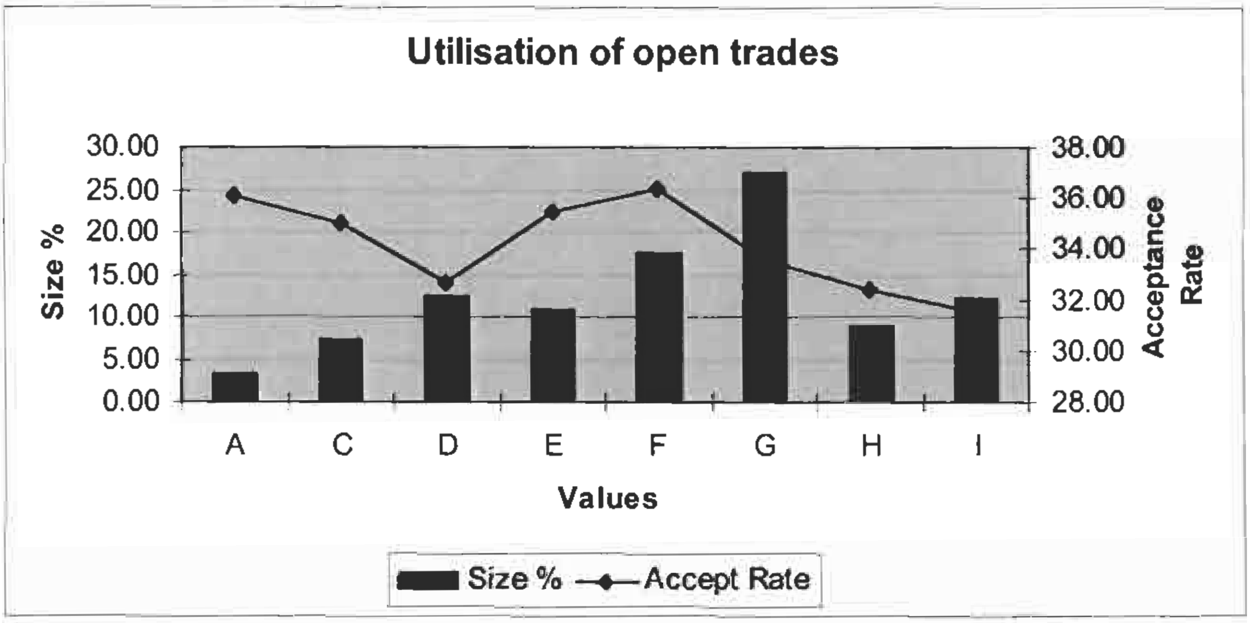
3.12.4. Utilisation of open trades

24 - Table 3.24: Utilization of open trades

Utilization of open trades	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
A_-4	215	380	595	3.37	36.13	3.6	3.3	0.09
C_00	446	827	1273	7.22	35.04	7.4	7.1	0.04
D_0.1-25.0	720	1482	2202	12.49	32.70	12.0	12.7	-0.06
E_25.1-40.0	683	1241	1924	10.91	35.50	11.4	10.7	0.07
F_40.1-60.0	1132	1977	3109	17.63	36.41	18.9	17.0	0.10
G_60.1-90.0	1606	3172	4778	27.10	33.61	26.8	27.3	-0.02
H_90.1-100.0	517	1076	1593	9.04	32.45	8.6	9.2	-0.07
I_100.1-HIGH	679	1478	2157	12.23	31.48	11.3	12.7	-0.12
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a differential correlation between acceptance rate and utilisation of open trades.

21 - Graph 3.21: Utilisation of open trades



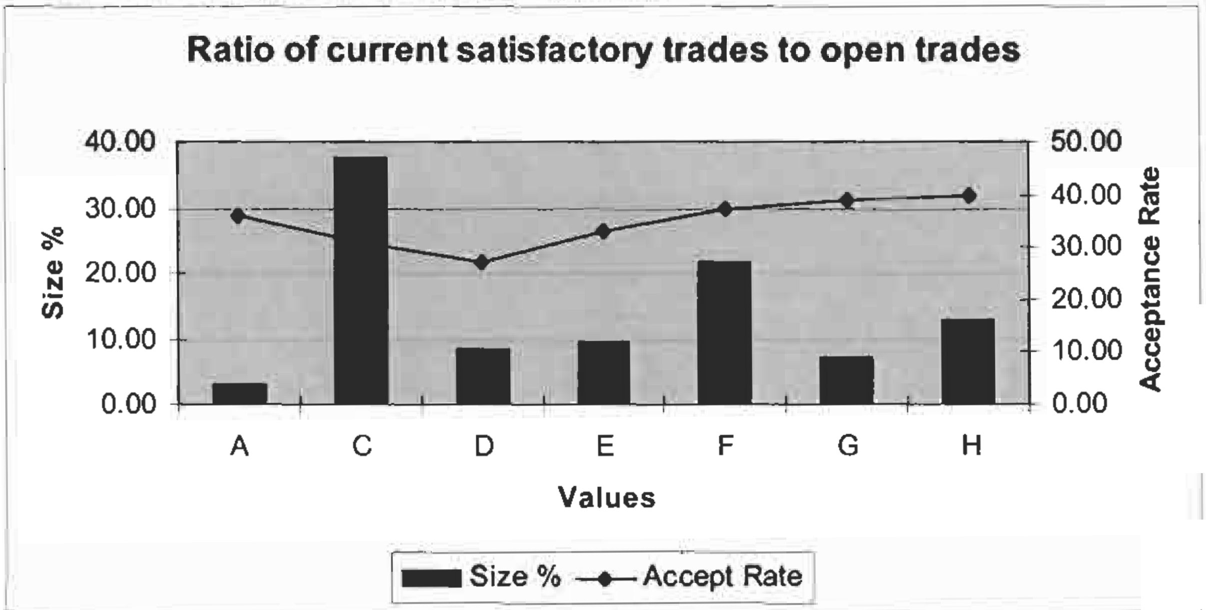
3.12.5. Ratio of current satisfactory trades to open trades

25 - Table 3.25: Ratio of current satisfactory trades to open trades

Ratio of curr. satisf. trades to open trades	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
A_-4	189	334	523	2.97	36.14	3.2	2.9	0.09
C_0	2052	4593	6645	37.69	30.88	34.2	39.5	-0.14
D_0.1-30.0	397	1069	1466	8.31	27.08	6.6	9.2	-0.33
E_30.1-40.0	548	1108	1656	9.39	33.09	9.1	9.5	-0.04
F_40.1-70.0	1414	2397	3811	21.62	37.10	23.6	20.6	0.13
G_70.1-99.9	494	768	1262	7.16	39.14	8.2	6.6	0.22
H_100	904	1364	2268	12.86	39.86	15.1	11.7	0.25
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

From category D upwards there is a positive correlation between current satisfactory trades and acceptance rate.

22 - Graph 3.22: Ratio of current satisfactory trades to open trades



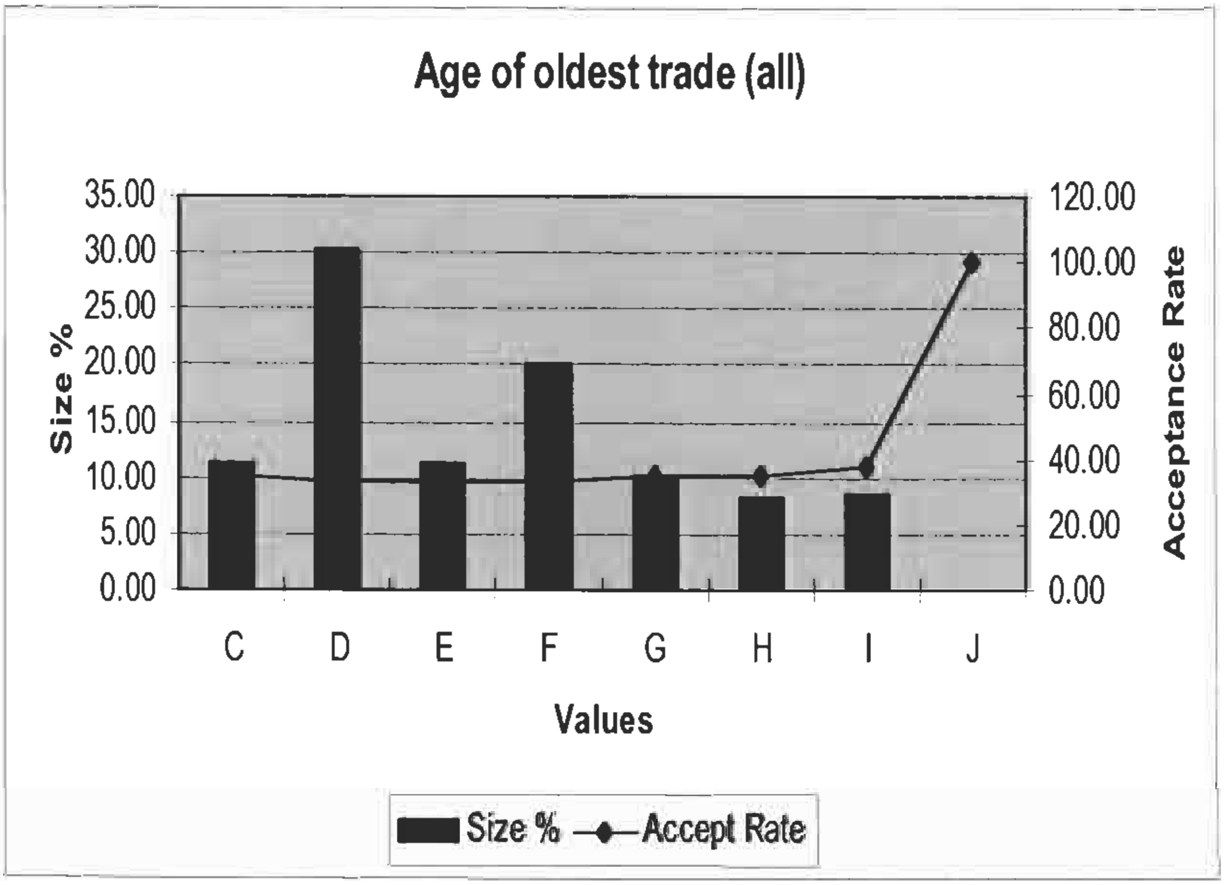
3.12.6. Age of oldest trade

26 - Table 3.26: Age of oldest trade

Age of oldest trade (all)	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
C_00-21	688	1294	1982	11.24	34.71	11.5	11.1	0.03
D_22-48	1776	3552	5328	30.22	33.33	29.6	30.5	-0.03
E_49-57	660	1335	1995	11.32	33.08	11.0	11.5	-0.04
F_58-83	1173	2397	3570	20.25	32.86	19.6	20.6	-0.05
G_84-108	629	1170	1799	10.20	34.96	10.5	10.1	0.04
H_109-139	506	959	1465	8.31	34.54	8.4	8.2	0.02
I_140-HIGH	565	926	1491	8.46	37.89	9.4	8.0	0.17
J_MISSING	1	0	1	0.01	100.00	0.0	0.0	-2.00
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is very weak correlation.

23 - Graph 3.23: Age of oldest trade



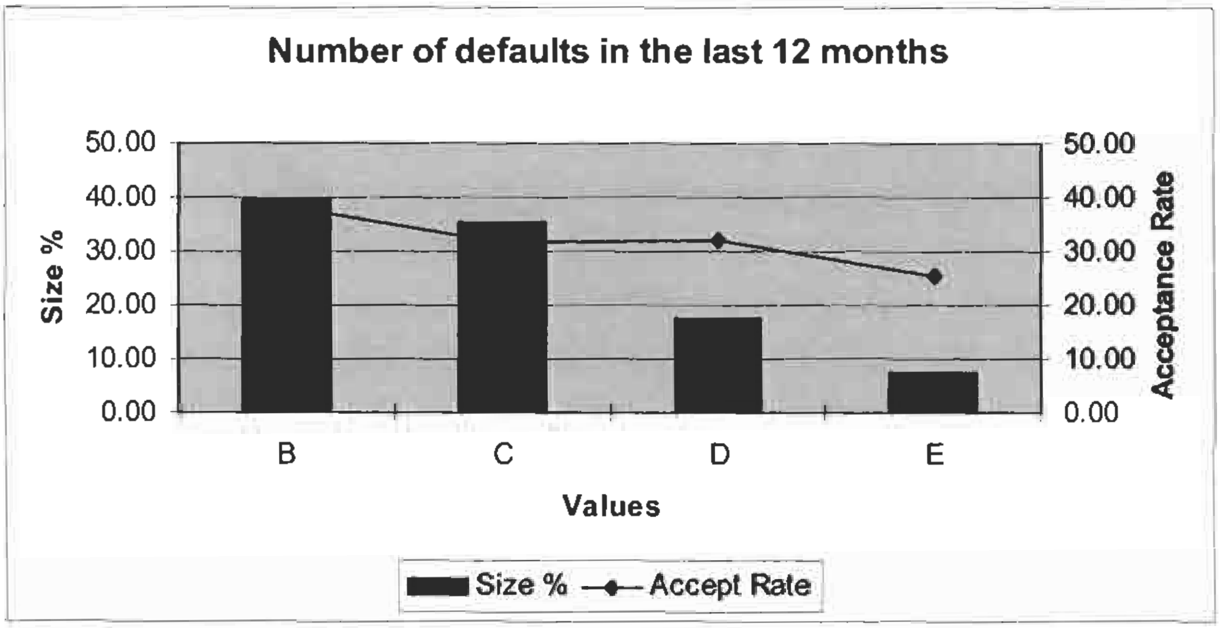
3.12.7. Number of defaults in the last 12 months

27 - Table 3.27: Number of defaults in the last 12 months

No. of defaults in the last 12 Mths	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
B_-02	2678	4286	6964	39.50	38.45	44.6	36.8	0.19
C_00	1990	4272	6262	35.52	31.78	33.2	36.7	-0.10
D_01	1002	2117	3119	17.69	32.13	16.7	18.2	-0.09
E_02-HIGH	328	958	1286	7.29	25.51	5.5	8.2	-0.41
Total	5998	11633	17631	100.00	34.02	100.0	100.0	0.00

There is a negative correlation between this characteristic and acceptance rate.

24 - Graph 3.24: Number of defaults in the last 12 months



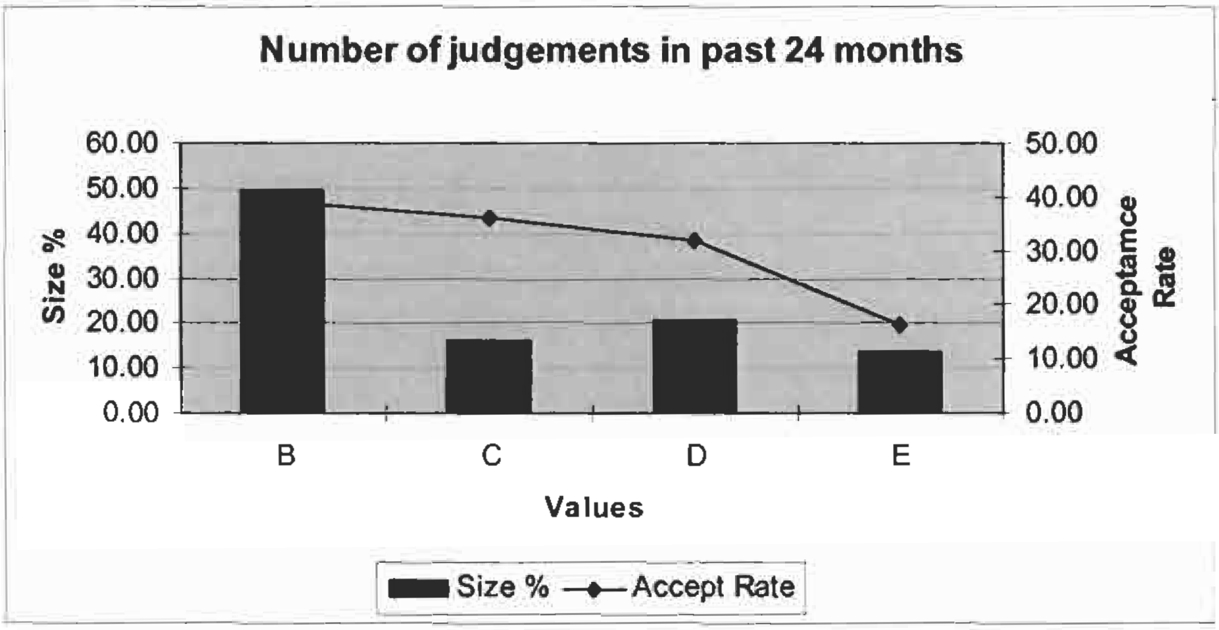
3.12.8. Number of judgements in the last 24 months

28 - Table 3.28: Number of judgements in the past 24 months

No. of judgements in the past 24 mths	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
B_-02	3398	5304	8702	49.36	39.05	56.7	45.6	0.22
C_00	1033	1830	2863	16.24	36.08	17.2	15.7	0.09
D_01	1166	2468	3634	20.61	32.09	19.4	21.2	-0.09
E_02-HIGH	401	2031	2432	13.79	16.49	6.7	17.5	-0.96
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a negative correlation between number of judgements and acceptance rate.

25 - Graph 3.25: Number of judgements in the last 24 months



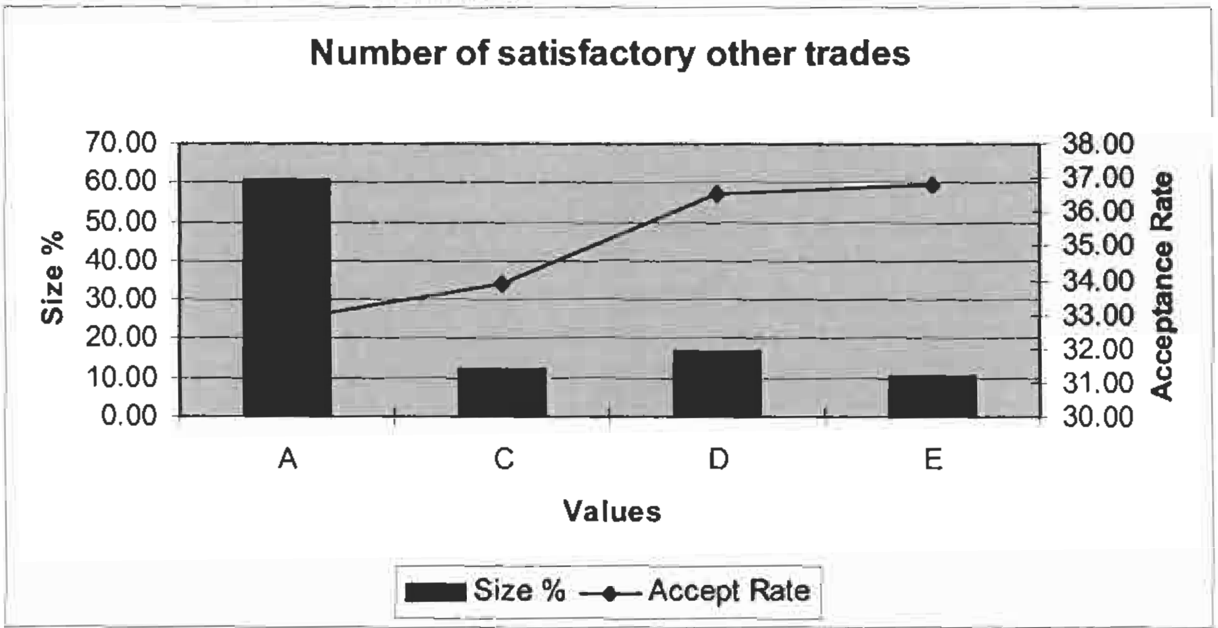
3.12.9. Number of satisfactory other trades

29 - Table 3.29: Number. of satisfactory other trades

No. of satisfactory other trades	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
A_-02	3524	7199	10723	60.82	32.86	58.8	61.9	-0.05
C_00	715	1395	2110	11.97	33.89	11.9	12.0	-0.01
D_01	1074	1863	2937	16.66	36.57	17.9	16.0	0.11
E_02-HIGH	685	1176	1861	10.56	36.81	11.4	10.1	0.12
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a significant positive correlation between the number of satisfactory other trades and acceptance rate.

26 - Graph 3.26: Number of satisfactory other trades



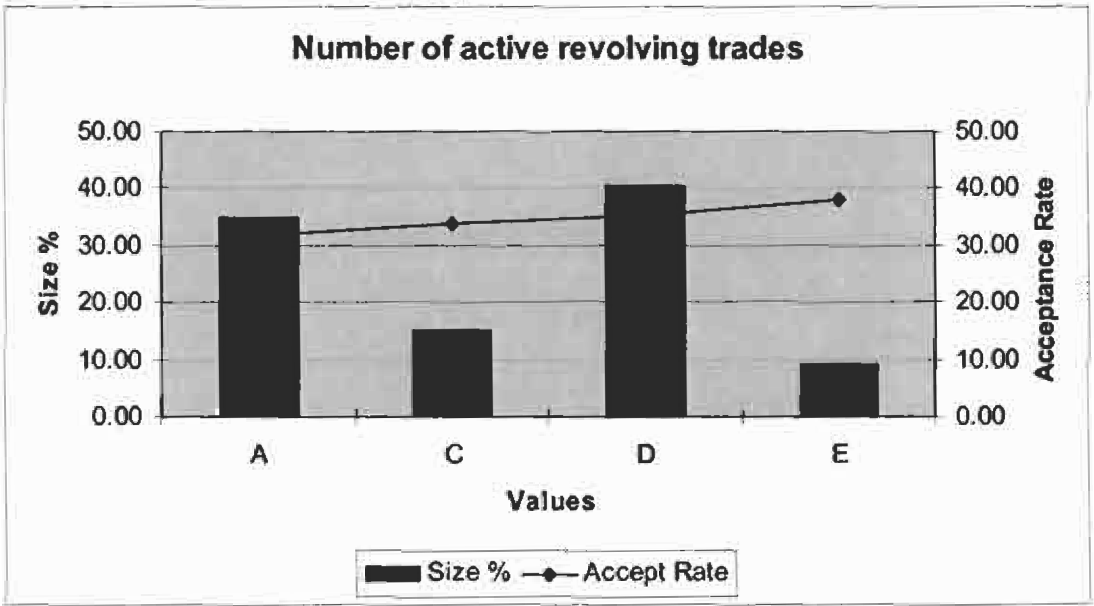
3.12.10. Number of active revolving trades

30 - Table 3.30: Number of active revolving trades

No. of active revolving trades	AR_Flag		Total	Size %	Acc Rate	Accept %	Reject %	WOE
	Accept	Reject						
A_-02	1960	4214	6174	35.02	31.75	32.7	36.2	-0.10
C_00	906	1774	2680	15.20	33.81	15.1	15.2	-0.01
D_01-02	2519	4651	7170	40.67	35.13	42.0	40.0	0.05
E_03-HIGH	613	994	1607	9.11	38.15	10.2	8.5	0.18
Total	**5998**	**11633**	**17631**	**100.00**	**34.02**	**100.0**	**100.0**	**0.00**

There is a positive correlation between this characteristic and acceptance rate.

27 - Graph 3.27: Number of active revolving trades



3.13. The results of characteristics not used in the scorecards

In order to restrict the length of the dissertation, the results of the characteristics not included in the scorecard were not discussed. These characteristics either did not show a significant statistical correlation with the propensity to pay or no relationship could be established.

The exact same approach was applied in the analysis of these characteristics and their exclusion has no impact on the value of the document since the focus is on the characteristics actually used.

3.14. Conclusion

Two sets of characteristics were analysed namely the application characteristics and the standard batch characteristics. Application characteristics were obtained from the credit application and SBC information were obtained from the credit report of the borrowers.

Two measures were used to analyse the characteristics. The first measure was bad rate which was calculated based on the payment history of the borrowers. The second measure was acceptance rate which was based on whether the loan application was accepted or declined by The Lender.

The results were tabulated and depicted as graphs for ease of interpretation. Only significant results were included.

CHAPTER FOUR

4. DEVELOPING A SCORING MODEL FROM THE RESEARCH DATA

4.1. Introduction

From the research data a scoring model was compiled for application characteristics as well as the standard batch characteristics. This was done by assigning a relevant score to each characteristic contained in the model. The 8 166 individuals in the development sample were then scored in terms of the two scoring models and from this a risk distribution profile was compiled. Two measurements were then used to evaluate how predictive these models are in terms of the development data. The measuring instruments used were the Receiver Operating Characteristic curve (ROC curve) and the Kolmogorov-Smirnov test. The two models were then cross-tabulated into a dual matrix format to get the best result from their respective predictive abilities.

4.2. The scorecard variables and values

Each variable (characteristic) in the scorecard has a set of values also known as attributes. The score that was assigned to each value is the result of multiplying the weight of evidence calculated with a factor which is produced by the statistical analysis software.

This factor is derived using a statistical software package which employs logistic regression to evaluate the predictive value that each characteristic contributes in terms of the total set of characteristics. A subset of characteristics were selected which yielded the best results and the less predictive characteristics were discarded. This is an iterative process (Siddiqi, 2006:73-134).

It is important to realise that the score assigned to each characteristic is a factor of its contribution to the total scoring model and if a specific characteristic is removed from the model the process has to be redone. This is because the characteristics are also valued in terms of the other variables and their collective contribution.

Also see item 3.8.3 for the meaning of the negative values of some of the SBC variables.

31 - Table 4.1: Application scorecard values

Variable	Values	Score
1. Loan Reason	New House	55
	Improvements	50
	Extensions	36
	Consumption	24
	Other	21
	Furniture	20
	Services	17
	Housing	5
	Business	2
	Cell Phone	0
	Education	0
2. Age	0 - 20	Policy decline
	21 - 25	0
	26 - 30	3
	31 - 35	23
	36 – 40	25
	41 - 45	45
	46 - 50	49
	51 - 58	63
	59 +	Policy decline
3. Bank name	ABSA	23
	FNB	1
	Standard Bank	0
	Other	0
4. Bank Account type	Savings	42
	Cheque	26
	Transmission	0
	None	0
5. Years at Work	0 – 6 months	Policy decline
	6 months – 3 years	0
	4 years – 12 years	27
	13+ years	44
6. Residential Postal Code	Group 1	84
	Group 2	59
	Group 3	42
	Group 4	25
	Group 5	18
	Group 6	0

32 - Table 4.2: SBC scorecard values

Variable	Values	Score
1. Number of trades opened in the last 24 months	-1	0
	0	17
	1	26
	2	7
	3+	0
2. Number of trades 3 months past due	-1	0
	0	36
	1	17
	2	16
	3	13
	4	11
	5	5
	6+	0
3. Number of enquiries in the last 24 months	-1	125
	0	119
	1	102
	2	87
	3-5	79
	6-8	63
	9-11	41
	12-13	30
	14-16	20
	17+	0
4. Utilisation of open trades	-4	52
	-1	0
	0	23
	0.1-25.0	57
	25.1-40.0	45
	40.1-60.0	42
	60.1-90.0	39
	90.1-100.0	15
	100.1+	0
5. Ratio of current satisfactory trades to open trades	-4	29
	(-1)-30.0	0
	30.1-40.0	15
	40.1-70.0	23
	70.1-99.9	35
	100	55
6. Age of oldest trade (measured in months)	(-4)-21	0
	22-48	8
	49-57	12
	53-83	17
	84-108	32
	109-139	38
	140+	82

Variable	Values	Score
7. Number of defaults in the last 12 months	-4	0
	-2	32
	0	17
	1	7
	2+	0
8. Number of judgements in the last 24 months	-2	35
	0	32
	1	23
	2+	0
9. Number of satisfactory other trades	-2	18
	-1	0
	0	0
	1	24
	2+	37
10. Number of active revolving trades	-2	11
	-1	0
	0	0
	1-2	48
	3+	36

4.3. The Risk Distribution

The development sample loans were scored using the newly developed application scorecard and the SBC scorecard. The results were summarised and are presented below.

Table 4.3 is the result of the application scorecard model and it shows the results of the 8 risk bands. The overall bad rate for the sample is 31.39%. Loans in band 1 have the lowest associated risk, with an average bad rate of 13.60%. Loans in band 8 have the highest associated bad risk, with an average bad rate of 46.83%. This means that clients in band 1 have a 13.6% chance of defaulting on their payments and clients in band 8 have a 46.83% chance of defaulting.

33 - Table 4.3: The Good/Bad/Indeterminate distribution for the application scorecard development sample

Band	Good (G)	Bad (B)	Ind (I)	Total Size	% of Good	% of Bad	% of Size	Cum. Good	Cum. Bad	Cum. Size
1	343	54	16	413	6.66	2.29	5.06	343	54	413
2	598	136	60	794	11.60	5.77	9.72	941	190	1207
3	1133	366	129	1628	21.98	15.52	19.94	2074	556	2835
4	1082	449	132	1663	20.99	19.04	20.36	3156	1005	4498
5	709	409	112	1230	13.76	17.35	15.06	3865	1414	5728
6	686	421	105	1212	13.31	17.85	14.84	4551	1835	6940
7	402	346	65	813	7.80	14.67	9.96	4953	2181	7753
8	201	177	35	413	3.90	7.51	5.06	5154	2358	8166
Total	**5154**	**2358**	**654**	**8166**	**100.00**	**100.00**	**1.00**			

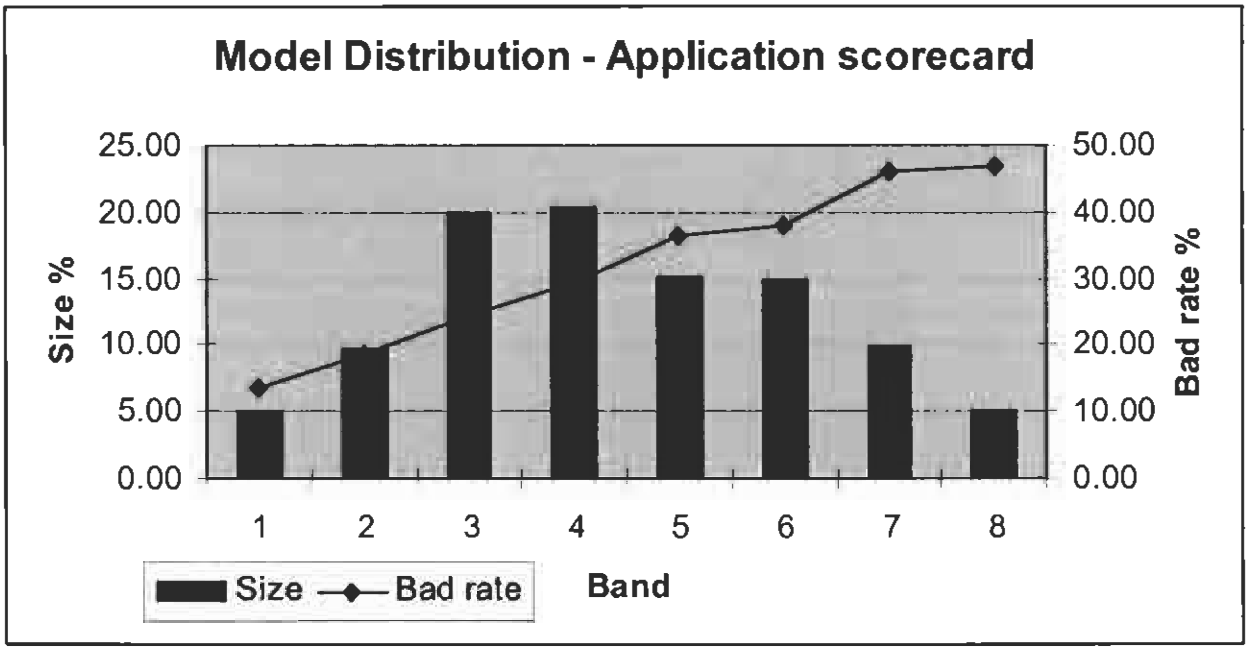
Table 4.3- continued

Band	Cum. % Good	Cum. % Bad	Cum. % Size	Bad Rate	Rel. BR	Min Score	Max Score	Gini Coeff.	KS stat
1	6.66	2.29	5.06	**13.60**	0.43	223	311	0.0015	0.0436
2	18.26	8.06	14.78	**18.53**	0.59	197	222	0.0120	0.1020
3	40.24	23.58	34.72	**24.42**	0.78	167	196	0.0695	0.1666
4	61.23	42.62	55.08	**29.33**	0.93	142	166	0.1390	0.1861
5	74.99	59.97	70.14	**36.58**	1.17	126	141	0.1411	0.1502
6	88.30	77.82	84.99	**38.03**	1.21	106	125	0.1834	0.1048
7	96.10	92.49	94.94	**46.26**	1.47	86	105	0.1328	0.0361
8	100.00	100.00	100.00	**46.83**	1.49	0	85	0.0751	0.0000
Total				**31.39**	**1.00**			**0.1228**	**0.1861**

When the results of Table 4.3 are depicted graphically in Graph 4.1 one can clearly see that the application scorecard model discriminates between loans based on the calculated bad rate.

The Lender would be able to use this model to reduce the risk of defaulters. For example, The Lender could choose to reduce the current bad rate by excluding borrowers with score band 7 and 8 in future. Applying this to the development sample would result in a decrease in loan volume of 15.02 % (9.96% + 5.06%). The new average bad rate of the development sample then decreases to (2 358-346-177) / ((2 358–346-177) + (5 154–402–201)) = 28.73% (see section 3.7.1.1. for bad rate formula).

28 - Graph 4.1: Model distribution of the application scorecard (good/bad)



The results of the SBC scorecard is shown in Table 4.4.

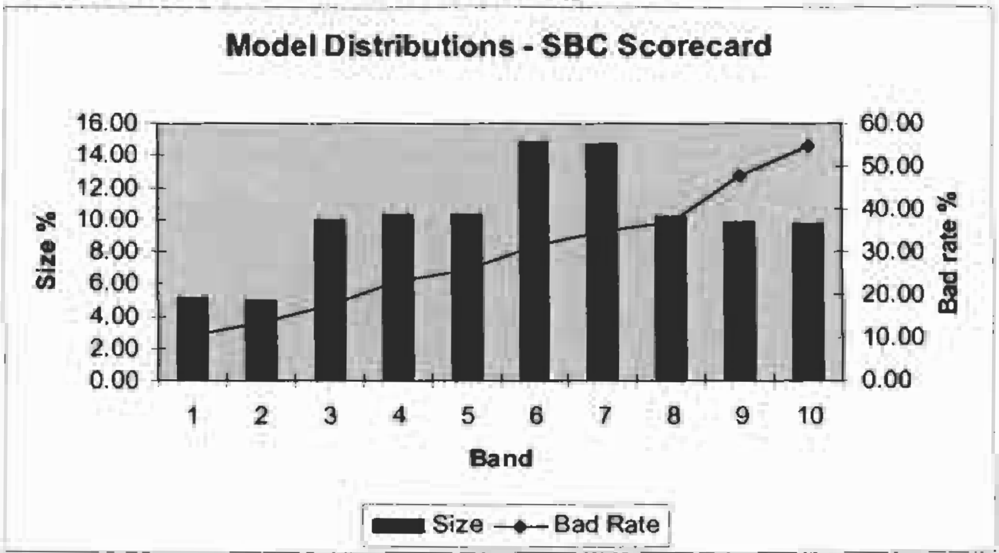
34 - Table 4.4: The Good/Bad/Indeterminate distribution for the SBC development sample

Band	Good (G)	Bad (B)	Ind (I)	Total Size	% of Good	% of Bad	% of Size	Cum. Good	Cum. Bad	Cum. Size
1	302	35	7	344	7.02	1.79	5.06	302	35	344
2	284	44	9	337	6.60	2.24	4.95	586	79	681
3	531	111	40	682	12.35	5.66	10.02	1117	190	1363
4	499	151	49	699	11.60	7.70	10.27	1616	341	2062
5	480	167	59	706	11.16	8.52	10.38	2096	508	2768
6	642	293	71	1006	14.93	14.95	14.79	2738	801	3774
7	586	312	102	1000	13.63	15.92	14.70	3324	1113	4774
8	384	225	87	696	8.93	11.48	10.23	3708	1338	5470
9	321	294	58	673	7.47	15.00	9.89	4029	1632	6143
10	271	328	62	661	6.30	16.73	9.71	4300	1960	6804
Totals	**4300**	**1960**	**544**	**6804**	**100.00**	**100.00**	**1.00**			

Band		Cum. % Good	Cum. % Bad	Cum. % Size	Bad Rate	Rel. BR	Min Score	Max Score	Gini Coeff.	KS stat
1		7.02	1.79	5.06	10.39	0.33	377	550	0.0013	0.0524
2		13.63	4.03	10.01	13.41	0.43	354	376	0.0038	0.0960
3		25.98	9.69	20.03	17.29	0.55	324	353	0.0169	0.1628
4		37.58	17.40	30.31	23.23	0.74	303	323	0.0314	0.2018
5		48.74	25.92	40.68	25.81	0.82	285	302	0.0484	0.2283
6		63.67	40.87	55.47	31.34	1.00	261	284	0.0997	0.2281
7		77.30	56.79	70.16	34.74	1.11	238	260	0.1331	0.2052
8		86.23	68.27	80.39	36.95	1.18	218	237	0.1117	0.1797
9		93.70	83.27	90.29	47.80	1.53	194	217	0.1131	0.1043
10		100.00	100.00	100.00	54.76	1.75	0	193	0.1155	0.0000
Totals					**31.31**	**1.00**			**0.1625**	**0.2283**

The results of Table 4.4 are presented in Graph 4.2. The graph illustrates that the SBC scorecard clearly discriminates between the various score bands based on bad rate.

29 - Graph 4.2: Model distribution of the SBC scorecard (good/bad)



The results of the accept/reject criteria for the SBC scorecard is given in Table 4.5.

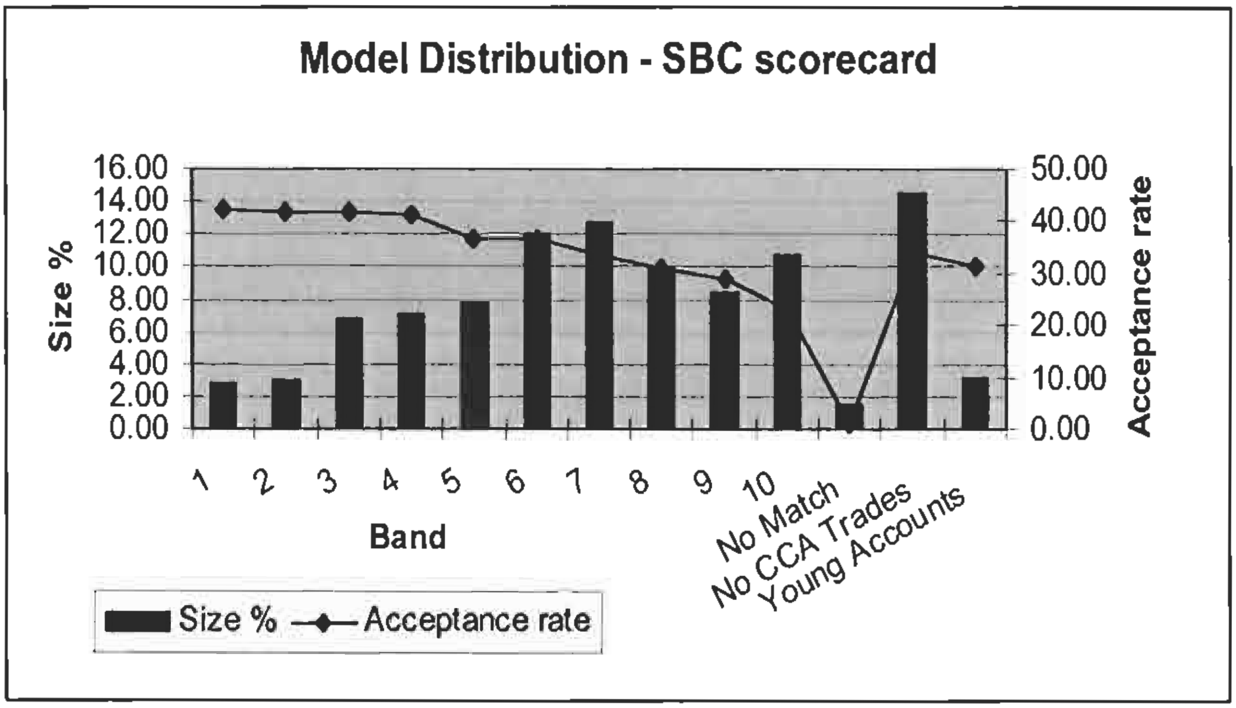
35 - Table 4.5: Accept/Reject distribution for the SBC validation sample

Band	Accept (A)	Reject (R)	Total Size	% of all Accept	% of all Reject	% of all Size	Cum. Accept
1	252	341	593	3.45	2.35	2.72	252
2	271	379	650	3.71	2.62	2.98	523
3	620	870	1490	8.50	6.00	6.84	1143
4	643	908	1551	8.81	6.27	7.12	1786
5	612	1062	1674	8.39	7.33	7.68	2398
6	958	1678	2636	13.13	11.58	12.10	3356
7	917	1838	2755	12.57	12.68	12.65	4273
8	660	1485	2145	9.05	10.25	9.85	4933
9	525	1290	1815	7.20	8.90	8.33	5458
10	540	1782	2322	7.40	12.30	10.66	5998
No Match	3	312	315	0.04	2.15	1.45	6001
No CCA Trades	1076	2070	3146	14.75	14.28	14.44	7077
Young Accounts	218	477	695	2.99	3.29	3.19	7295
TOTAL	7295	14492	21787	100.00	100.00	100.00	

Band		Cum. Reject	Cum. Size	Cum. %Accept	Cum. %Reject	Cum. %Size	Acceptance Rate (per band)
1		341	593	3.45	2.35	2.72	42.50
2		720	1243	7.17	4.97	5.71	41.69
3		1590	2733	15.67	10.97	12.54	41.61
4		2498	4284	24.48	17.24	19.66	41.46
5		3560	5958	32.87	24.57	27.35	36.56
6		5238	8594	46.00	36.14	39.45	36.34
7		7076	11349	58.57	48.83	52.09	33.28
8		8561	13494	67.62	59.07	61.94	30.77
9		9851	15309	74.82	67.98	70.27	28.93
10		11633	17631	82.22	80.27	80.92	23.26
No Match		11945	17946	82.26	82.42	82.37	0.95
No CCA Trades		14015	21092	97.01	96.71	96.81	34.20
Young Accounts		14492	21787	100.00	100.00	100.00	31.37
TOTAL							33.48

The results of Table 4.5 are presented in Graph 4.3 below. The graph clearly shows how the model discriminates between the various score bands based on the acceptance rates.

30 - Graph 4.3: Model distribution of the SBC scorecard (Accept/reject)



4.4. The receiver operating characteristic curve (ROC)

The receiver operating characteristic curve (ROC curve) is a graph that plots the true positive rate against the false positive rate for the different possible cut points of a diagnostic test.

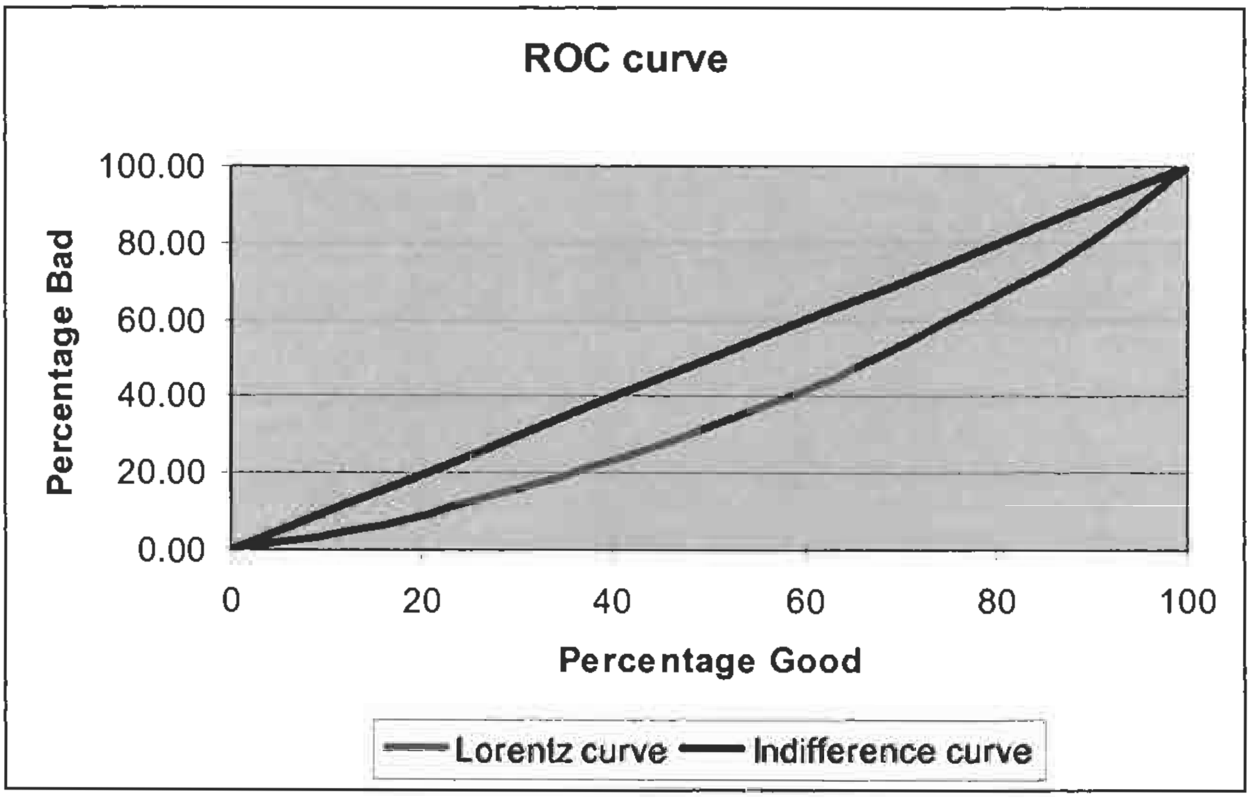
A ROC curve demonstrates several things:

- It shows the trade-off between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
- The closer the Lorentz curve follows the bottom axis and then the right-hand axis (i.e. the sides of the triangle formed with the indifference curve as the diagonal side) the larger the ROC space (i.e. the area between the indifference curve and the Lorentz curve) and the more accurate the test.
- The closer the Lorentz curve comes to the 45-degree diagonal (the indifference curve) the smaller the ROC space and the less accurate the test.
- The slope of the tangent line at a cut point gives the likelihood ratio (LR) for that value of the test.
- The area under the curve is a measure of test accuracy.

The gini coefficient is the calculated area between the Lorenz curve and the indifference curve. It is an indicator of the discriminatory ability of the model (Wikipedia, 2006).

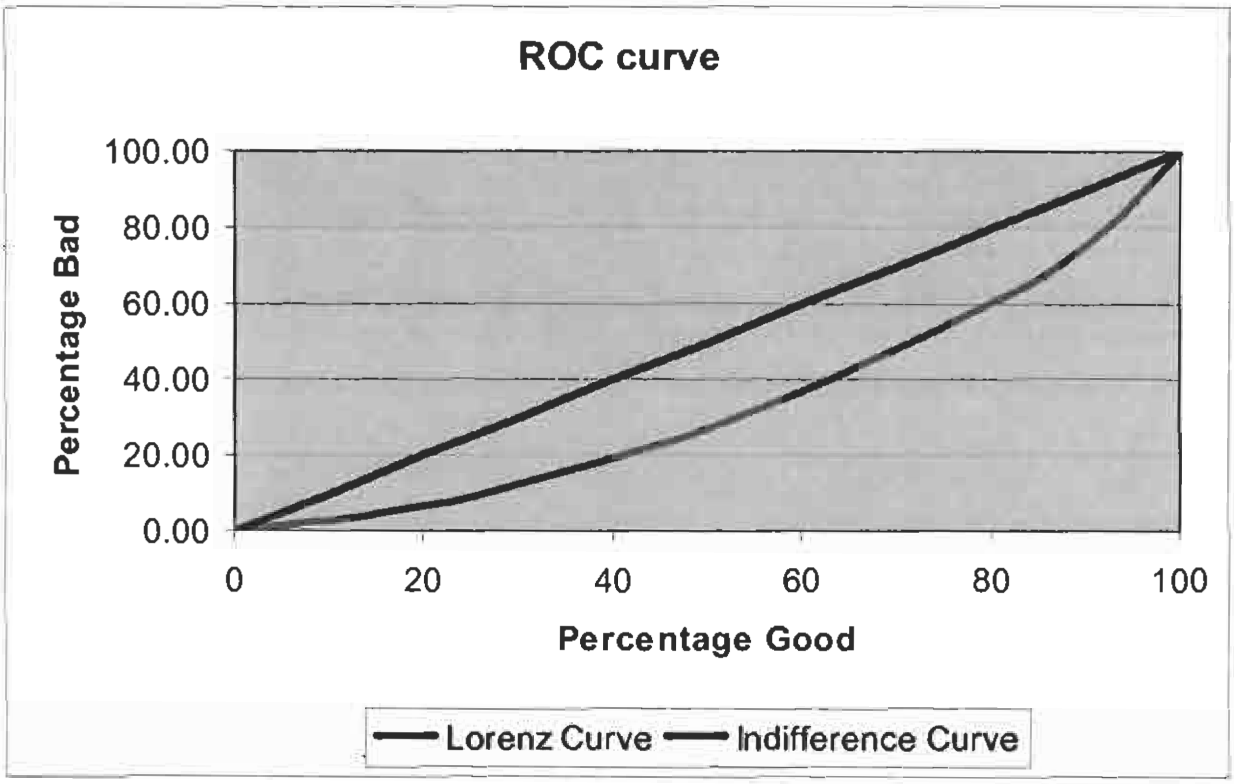
The application characteristic scorecard model (Graph 4.4) has a gini coefficient of 0.12. This could be considered as being low, but the limitations in the data restrict the predictive ability of the model. As the data fields become more populated in future, the predictive ability of the model will increase.

31 - Graph 4.4: ROC curve of the application scorecard development sample



The SBC scorecard has a gini coefficient of 0.16 which is higher than the application scorecard. The ROC curve for the SBC scorecard is depicted in Graph 4.5.

32 - Graph 4.5: The ROC curve for the SBC scorecard development sample



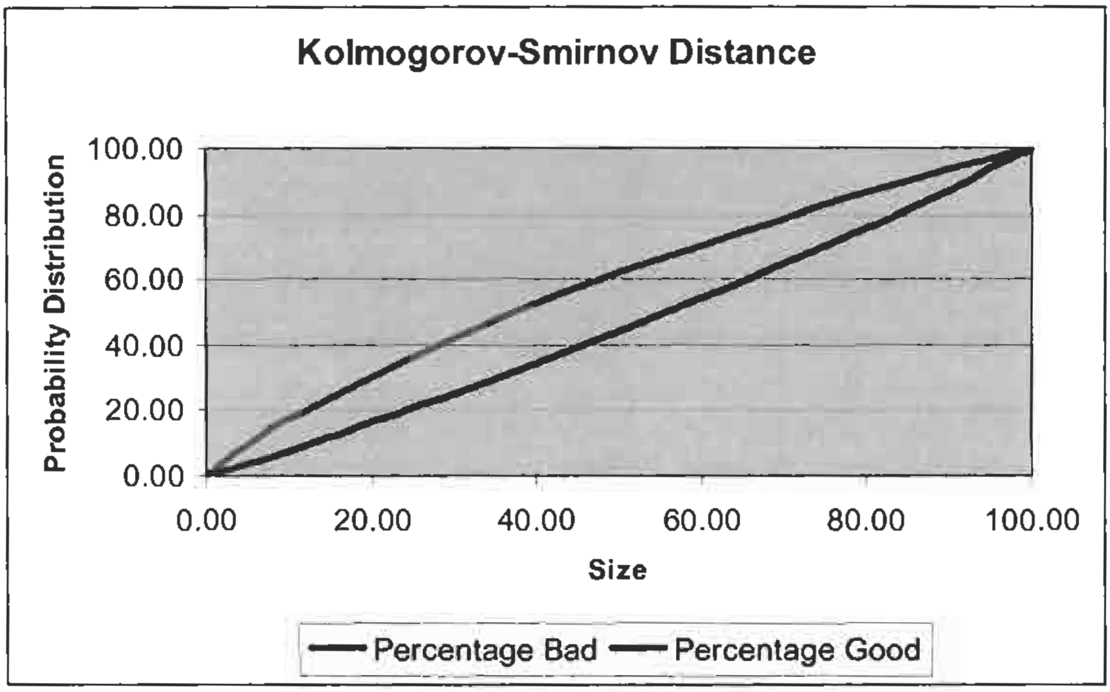
4.5. The Kolmogorov-Smirnov test (KS test)

The Kolmogorov-Smirnov test (KS test) is used to determine whether two underlying probability distributions based on finite samples differ.

The two-sample KS test is one of the most useful and general nonparametric methods for comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples.

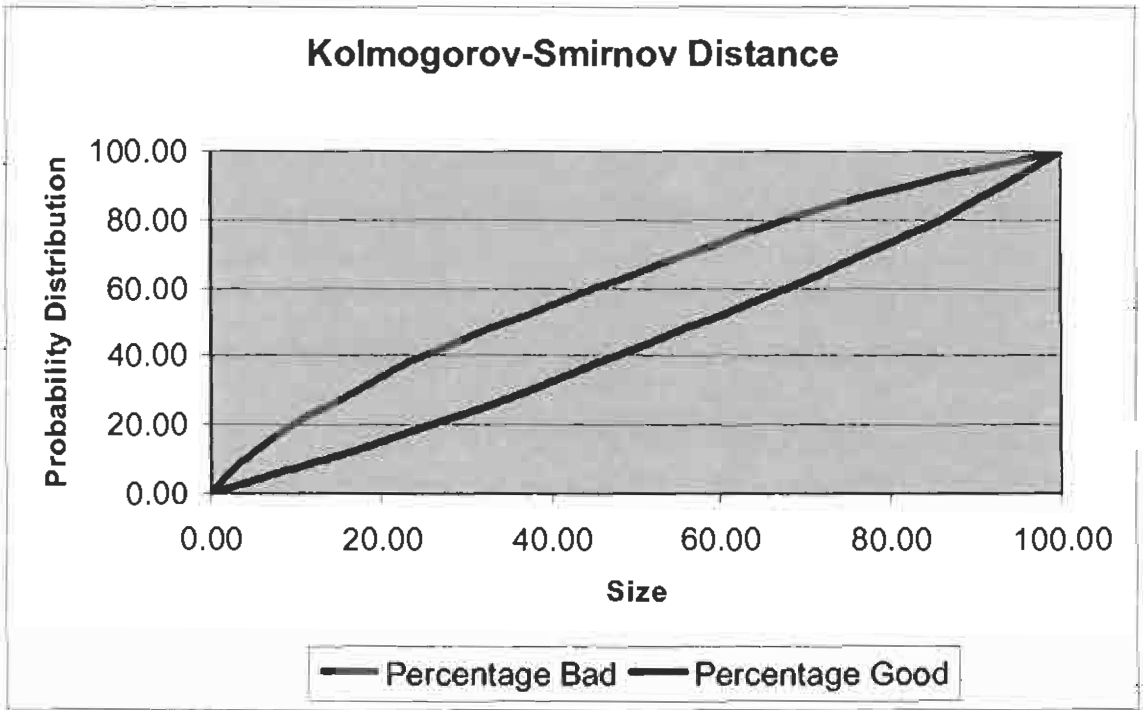
The KS distance is calculated as the maximum distance between the "cumulative percentage good curve" and the "cumulative percentage bad curve" (Wikipedia, 2006). In Graphs 4.6 and 4.7 the KS distance is the area between the grey line (percentage bad) and the black line (percentage good). If the area between the grey line and the black line was equal to zero, it would mean that there was no discrimination between good and bad. Similarly the bigger the area between the two lines the better the discrimination between good and bad in the model. The application scorecard model rendered a KS distance of 0.18. This could also be considered as being low, but once again this is due to the limitations in the data and as the data fields are populated it will lead to a higher KS value.

33 - Graph 4.6: The KS Distance for the Application scorecard



The SBC scorecard rendered a KS distance of 0.23 (Graph 4.7) which is higher than that obtained by the application scorecard.

34 - Graph 4.7: The KS Distance for the SBC scorecard



4.6. Using a dual matrix

The application risk scorecard should be used in conjunction with the SBC risk scorecard in a dual score matrix when determining the final approval decision.

A dual matrix is the cross-tabulation between the bands of the two scorecards (Siddiqi, 2006:145). The dual matrix is developed by grouping cells with similar characteristics such as bad rate and approval rate together. Each set of cells is then assigned a risk category (for example high, medium and low risk).

The dual matrix for The Lender was shaded with three approval bands and one rejection band (Table 4.6).

Product assignment will be done using the risk group from the dual score matrix.

36 - Table 4.6: Dual Score matrix with 3 risk groups

	Application band							
SBC Band	1	2	3	4	5	6	7	8
1	LR	LR	LR	LR	LR	LR	LR	AR
2	LR	LR	LR	LR	LR	LR	LR	AR
3	LR	LR	LR	LR	LR	LR	AR	AR
4	LR	LR	LR	LR	LR	AR	AR	HR
5	LR	LR	LR	LR	AR	AR	AR	HR
6	LR	LR	AR	AR	AR	AR	AR	HR
7	LR	LR	AR	AR	AR	AR	HR	HR
8	AR	AR	AR	AR	HR	HR	HR	D
9	HR	HR	HR	HR	HR	HR	D	D
10	HR	HR	HR	HR	D	D	D	D
No Match	D	D	D	D	D	D	D	D
No CCA	AR	AR	AR	AR	HR	HR	HR	D
Young Accounts	AR	AR	AR	AR	HR	HR	HR	D

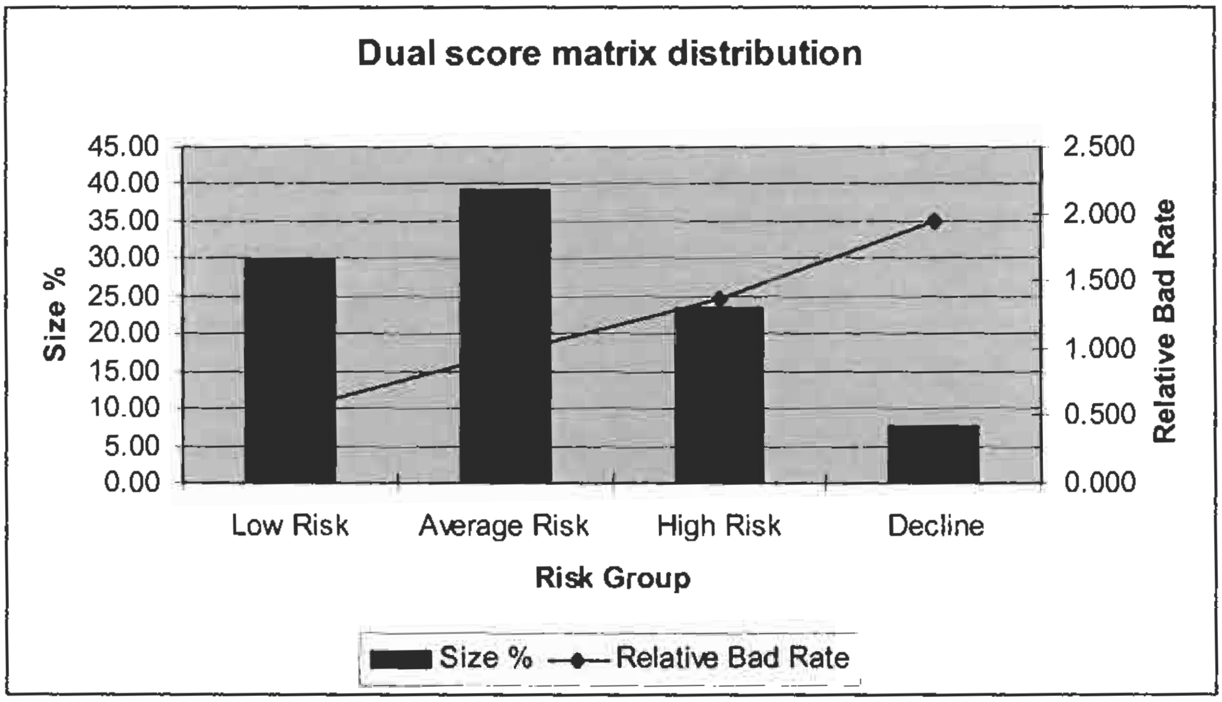
The development data was then assessed by the dual score matrix and the results are listed in Table 4.7.

37 - Table 4.7: Distribution of dual score matrix risk groups

Group	Bad	Good	Indet.	Total	Size%	Bad Rate	Rel. Bad Rate
Low Risk (L R)	384	1915	138	2437	29.84	16.70	0.532
Average Risk (A R)	886	2042	274	3202	39.21	30.26	0.964
High Risk (H R)	744	978	186	1908	23.37	43.21	1.376
Decline (D)	344	219	56	619	7.58	61.10	1.947
Total	2358	5154	654	8166	100.00	31.39	1.000

The results in Table 4.7 were presented in Graph 4.8. The resulting graph clearly illustrates how the relative bad rate increases for the different risk groups.

35 - Graph 4.8: The Distribution of the dual score matrix



4.7. Caution about the use of the developed scorecards

A note of caution has to be made at this time. One must realise that the scorecard characteristics are biased by the business rules and specific set of circumstances that apply to The Lender from which the sample was taken.

These scorecards were designed to minimise the portfolio risk of The Lender and should they be used by another institution, they will not yield the same results.

A good example to illustrate this is found in the use of the "bank name" characteristic. The Lender has a specific preference for clients with ABSA accounts; this is due to a specific payment mechanism available to The Lender for ABSA account holders. This mechanism yields better than average collection results for The Lender and subsequently the scoring model will reflect that.

It should be clear from the above example that a scoring model developed with data from a specific source should be used only for that institution.

The value for another institution would lie in following the same approach and the methods that were applied, to develop their own scorecards which are in tune with their specific business rules and circumstances. Such a scorecard would yield the desired reduction of portfolio risk.

4.8. Conclusion

Each of the characteristics was assigned a value based on the weight of evidence calculated in the tables. The scorecards were then tested by applying them against the sample data.

The results show how the scorecards band together the different borrowers into risk bands; it also shows how the bad rate increases across the bands.

The ROC and KS tests were then applied to measure the predictive ability of the scorecards and the conclusion was that the scorecards do effectively discriminate. An improvement is expected as the data becomes better populated.

It is recommended that the two scorecards be used together in a dual matrix to get the best result.

CHAPTER FIVE

5. RECOMMENDATIONS AND CONCLUSION

5.1. Introduction

Credit scoring is a tool which should be deployed in a holistic manner. It is an ongoing process of assessment and improvement, not only of the scorecard but also of all the underlying business rules and processes that impact on credit risk. It is recommended that scorecards should be deployed within a framework of a credit policy.

5.2. Additional Fields

The scorecards developed in this dissertation should only serve as intermediate scorecards. The Lender is advised to capture additional fields that may be included at a later stage. Scorecard variables should be mandatory fields on the application form. The following fields are recommended to become mandatory fields for the future improvement of the application scorecard.

- **Marital Status:**
  - Married
  - Widowed
  - Divorced
  - Single

- **Number of dependents:** Although this field is currently captured, there was a high number of missing values in the development sample. In future, if the field is not supplied by the applicant, the value 0 should not be assigned. An alternative value such as -1 should be used as the default value.

- **Phone:** It is recommended that the landline numbers (home and work) be captured as separate fields. It is also strongly advised to capture the mobile phone number as a separate field.

- **Years at address:** It is recommended to add this variable. This variable might be used in either policy rules or in the scorecard.

- **Residential status:** It is advised that a new field be added for the residential status. This field should comprise of the following possible values:
  - Owner
  - Tennant / Renting
  - Living with parents
  - Living with employer
  - Boarding
  - Hostel

- **Employment type:** It is recommended to add this field and to limit the potential responses, i.e. free text should not be allowed.
  - Full time
  - Part time
  - Self employed
  - Contract worker
  - Pensioner
  - Unemployed

- **Occupation:** This field is currently captured as free text. It is recommended to create a fixed list of possible occupations.
  - Executive
  - Office (High)
  - Office (Medium)
  - Office (Low)
  - Management
  - Supervisor
  - Skilled Worker
  - Semi-skilled Worker
  - Unskilled Worker
  - Junior Position
  - SAPS

- Correctional Services
- Military
- Security
- Department of Health
- Department of Education
- Other Government Department
- Professional Medical
- Professional Engineering
- Professional Science
- Professional Education
- Professional Legal
- Professional Finance
- Professional Other
- Ministry Services
- Pensioner
- Retired
- Driver
- Student
- Sales
- Housewife
- Self-employed
- Unemployed
- Farmer
- Trades
- Consultant
- Other
- Unspecified

It is advised that the choices for the variable "purpose of loan" be extended. This is due to the fact that 44% of applicants specify "other" as the purpose for the loan. Possible additional choices include:

- Debt Repayment
- Funeral
- Emergency

- Medical
- Clothing

Intermediate scores could be assigned until sufficient information is gathered on the new values; once sufficient performance history has been recorded these values should be reassessed.

5.3. Develop a credit policy

It is important to realise that credit scoring on its own will not achieve any significant improvement in a credit provider's risk management if it does not form part of a carefully formulated credit policy (Fair Isaac Companies, 2001:8).

If such a policy is in place and before credit scoring is employed, the following questions have to be answered:

- Do you expect to reduce bad debt? If so, by how much?
- Do you expect to increase volume? If so, by how much?
- Do you want to improve control over the credit approval process?
- Do you want to streamline credit operations?

Once the goals have been clarified, policies regulating the use of the scorecard can be set. The following is a list of scoring-related issues which are of importance to a credit policy strategy:

- Which applications should not be scored (i.e. policy decisions)?
- How should one handle applications where scored information is missing?
- Where should the cut off score be set?
- What in-house information (if any) should one use?
- What information (if any) should one verify?
- What strategy should one employ for setting credit limits or loan amounts and terms?
- How should one determine the appropriate reasons for rejection?

A scorecard is developed based upon previous applicant information and payment history of a specific client base. Should there be a shift in the client base, for example due to a change in marketing policy, the scorecard has to be recalibrated. Or, if certain events occur infrequently, such as applicants who have major adverse information or judgements in their credit bureau report, a scorecard will generally be unable to assign the appropriate score to that applicant (e.g. penalise them severely enough). Such infrequent situations are outside the scope of a scorecard development and are therefore most appropriately handled with credit policy. Examples of areas where credit policies should be employed are discussed below.

5.3.1. Default credit information

According to the Fair Isaac Companies (2001: 9) most creditors reject applicants with major default credit information or judgments and adverse listings on their credit bureau report, regardless of how they might score. The use of generic credit bureau scorecard characteristic helps alleviate some of the concerns surrounding the scores of applicants with negative credit information at the bureau. However, a sound credit policy is still needed to automatically reject such applicants that otherwise would pass a cut-off credit score.

5.3.2. Affordability

Even if the regulatory requirement in terms of the NCA did not exist, the measurement of the ability to repay a loan is an important credit policy aspect. For example, two applicants applying for a similar loan might both have the same score, but the one earning a bigger income might be accepted while the other is declined. Most creditors use either debt ratio or income as a measure of capacity to repay. These factors are often analysed in scorecard development, and may be components of the scorecard. However, creditors typically look for some explicit measure of an applicant's ability to repay the loan. Because debt ratio ignores relative income level and income ignores debt burden, some measure of disposable income is generally preferred.

5.3.2.1. Analysis of current affordability assessment practices

The most appropriate tool that can be utilised in conjunction with a credit scorecard to ensure that a borrower will not be over extended by a lender is an affordability assessment. The example given in Table 5.1 resulted from studying the affordability calculation methodologies of three microfinance industry companies and a consultant employed by the MFRC to audit microlenders on reckless lending. The common elements and the best practices observed are listed below.

The most common elements observed are:

- Clients are expected to submit a copy of their identity document, their latest payslip and at least one month's bank statements.
- The credit bureaus are queried to obtain available credit information on the client.
- The client's credit commitments on the National Loan Register (NLR) as well as the Consumer Credit Association (CCA) register are taken into account.
- The bank statement is analysed to identify regular financial commitments that are not reflected on the NLR and CCA such as insurance payments.
- The payslip is analysed to determine regular monthly income.
- Loan applications contain a declaration of regular monthly expenditure other than those observed on the bank statement, payslip and from the credit bureau (NLR and CCA). These declared expenses are taken into account to calculate the net available income.

The best practices observed are:

- Bonuses and non regular income are not taken into account when calculating the net income.
- A rule with regard to the instalment size is usually applied. This is done by capping the maximum allowable loan instalment as a percentage of the gross or net salary.
- Where a client's declared expenses are below a certain threshold a minimum value is taken.

If employed properly this affordability assessment will enable lenders to identify over extended borrowers and prevent them of being found guilty of reckless lending as defined by the NCA.

38 - Table 5.1 Example of an Affordability Calculation

Example of an Affordability Calculation

	1. SNI Calculation (Statutory net income)		
	Income:		
A	Gross Income	6000	
	Statutory Deductions:		
B	Tax (PAYE)	1250	
	UIF	50	
	Pension	260	
	Other	0	
C	**Total**	1560	
D	**SNI (Statutory Net Income)**	4440	A - C = D
E	**First instalment value**	**888**	Calculation of an instalment ceiling as % of the SNI (D x 20% = E) The new instalment may not be greater than this amount.
	2. Disposable income calculation		
F	Non Regular income on payslip	1000	Identify non regular income that is included in the gross income
G	Adjustment for tax on **F**	208	Calculate tax paid on non regular income (B / A) x F = G)
H	**Adjusted SNI**	**3648**	D - F + G = H
	Payslip deductions:		
	Medical Aid	200	
	Insurance	200	
	Loans	300	
	Other	150	
J	**Total**	**850**	
K	**Nett regular take-home pay**	**2798**	H - J = K
	Bank Statement deductions:		
	Medical Aid	500	
	Insurance	200	
	Loans	0	
	Other	150	
L	**Total**	**850**	
	Other Expenses:		
	CCA Payments	100	CCA payments not already on bank statement or payslip
	NLR Payments	150	NLR payments not already on bank statement or payslip
	All expenses declared by Client	750	A default minimum must be applied here to compensate for non disclosure by clients (R 750 is often used)
M	**Total**	**1000**	
N	**Second Instalment value**	**948**	K - L - M = N The new instalment may not be greater than this amount.
O	**Maximum instalment value**	**888**	**Select smallest value of E or N**

5.3.3. Fraud

Scorecards are developed mainly to measure credit risk and are not specifically fraud prevention tools. Therefore, a policy should be in place to reverse a scorecard's decision when a high-scoring applicant's existence cannot be verified or if other information indicates fraud.

5.3.4. Missing applicant information

Before an application is scored, it has to be checked for completeness. Clear business rules should exist should information be missing from the application. It is recommended that all the necessary information is obtained from the applicant. The practice of using a "not given" attribute point value for missing characteristics in the scorecard is not recommend and if applied should be restricted to no more than one item.

5.3.5. The cut-off score strategy

Setting a cut-off score involves a trade-off between acceptance rate and risk. Acceptance rate is the volume of applicants accepted and risk is the number of bad accounts among those applicants. Finding the cut-off score is a function of the goals set for these two parameters (Fair Isaac Companies, 2001:10).

Although one cannot determine the cut-off before receiving the scorecard and accompanying data, one needs to decide how to determine the cut-off score ahead of time. There are two possible approaches to setting the cut-off score:

- Set the cut-off score so that the projected acceptance rate is the same as before the installation of the scorecard. Setting the cut-off score in this manner allows one to reduce the bad rate of the accepted accounts while trying to maintain a similar acceptance rate.
- Set the cut-off score at some point between the following scores: the score at which the projected acceptance rate is the same as before the installation of the scorecard. This method results in the approval of more accounts, with a lower percentage of bad accounts being accepted than before the installation of the scorecard.

When developing a custom scorecard, one also receives basic statistics from the development sample. Using this data, the acceptance rate can be estimated as well as the corresponding percentage of accounts expected to default at a particular cut-off score.

Scorecards are developed from historic data and because circumstances change over time, scorecard development statistics should only be viewed as rough estimates of expected performance. Credit scores reflect a relative ranking of applicants, i.e. higher scoring applicants can be expected to perform better than lower scoring applicants. This should not be confused with a high score band which would indicate a risky client. For example, in the application scorecard a client in band eight has a lower credit score than a client in band one. However, a review of actual results will provide a more accurate projection of acceptance and bad rates by score.

5.3.6. Historic payment information

A client's payment history of a previous account is an important factor, and should be considered in the credit decision-making process regardless of whether it is a scored characteristic. It should be decided how this is to be used, and how and when it will be made available. If previous experience is considered and it is not a scored characteristic, decisions contrary to the final score should be treated as overrides, and recorded and tracked accordingly.

5.3.7. Verification of applicant information

When verifying applicant information, consider the number of verification failures over a period of time and decide if the cost of checking justifies the potential savings. If verification is justified or desired, verify after the application is scored. A cost saving may be experienced for applications scoring below the cut-off which are rejected and therefore do not need verification.

5.3.8. Develop an override strategy

An override is a judgmental reversal of the decision indicated by the score, such as rejecting an applicant who scores above the cut-off or accepting an applicant who scores below the cut-off. These overrides are also referred to as low side overrides, when the applicant fails the scoring but is passed and high side overrides when the applicant passes the scoring but should fail. While there may be good reasons to develop an override strategy it is recommend that this be applied very selective and very specific when developing this strategy. If overrides are made too often it can impact negatively on the scoring results. A reasonable override strategy should be based on clearly defined guidelines that are consistently applied. Unwise overrides are based on "feel" or intuition, or not liking the "looks" of an application. The elements of a successful override strategy consist of defining and enforcing guidelines, and evaluating results. As a rule of thumb the combination of high and low side overrides should never exceed 15%.

5.3.8.1. Define guidelines

In formulating an override strategy, consider the following:

- Allow only overrides based on specific information and not on the "look" or "feel" of an application.
- Allow overrides that use information not used by the scorecard.
- Do not use scorecard characteristics as override reasons, or use information already taken into account by the scorecard.
- Only allow overrides that can be consistently implemented.
- Decide what authority level is needed for override approval.
- Regularly evaluate the effectiveness of the override reasons.

5.3.8.2. Monitor decisions

Override decisions should be carefully monitored to ensure that the guidelines are being appropriately applied:

- Each override reason should be assigned a code that clearly identifies it.
- This code should be retained in the master file record for low side overrides, as well as in the reject records for any high side overrides.
- Too frequent use of a "general" or "miscellaneous" override category may be an indication of abuse of the override guidelines.

5.3.8.3. Evaluate the Strategy

Based on the performance of loans that were approved from below the cut-off point, one can evaluate effective and ineffective overrides. Tracking the effectiveness of overrides above the cut-off point is more difficult. It requires some portion of these applicants to be approved (in effect overriding the override) to determine the effectiveness of the above cut-off declines.

The reason for the original override (why the applicant would have been rejected) should be recorded on the master file to support this analysis. Based on the results of this tracking the override strategy could be adjusted in future. However, even when overrides "improve" the results achieved with the scorecard, additional costs (in terms of credit analyst review time and credit bureau expense) and lengthened application turnaround time, may outweigh the gains from making overrides.

5.3.9. Set credit limits, or loan amounts and terms

An applicant's score is not an index for setting initial credit limits or loan amounts and loan terms. As a risk measure, however, the applicant's score can be weighed against his/her capacity to pay (e.g. income, debt ratio) in determining credit limits or loan amounts. In such strategies, the value of the loans at risk are lower if a smaller limit or loan amount is established for low-scoring applicants than if no rule is applied.

The credit score can also be integrated into the assignment of a loan amount. For example, an account that would receive a "high" limit from the current assignment method, but that scored relatively low (right above cut-off), could be given a "medium" limit instead.

The credit score can also be used to help determine the amount of down payment, collateral or deposit required. This should however always be tested for reasonableness and to ensure that the desired result is obtained. For example, in the case of revolving accounts, if credit limits are set too low it may have the unwanted effect of reducing activity levels.

Scorecards are built on information to which some established rules were applied and any significant change in the rules may impact the scorecard's effectiveness.

5.4. Scorecard and portfolio monitoring

Scorecard and portfolio management reports are associated with portfolio and scorecard performance statistics, such as approval rates, bad rates and override rates. They are important tools to ensure that the company's objectives in terms of portfolio risk are achieved.

The use of the following scorecard and application reports are suggested:

- Scorecards assume that the future will be like the past, in order for this assumption to remain valid the following aspects needs to be monitored on an ongoing basis.
    - System stability (also known as population stability and scorecard stability).
    - Scorecard characteristic analysis.
    - Non scorecard characteristic analysis.

- It is also important to monitor and pinpoint the following sources of change in the profiles of applicants and approves.
    - Scorecard and non scorecard characteristic analysis.
    - Analysis of competition and their marketing campaigns.
    - Analysis by region and other segments.

- Tracking the risk profiles of incoming customers and applicants.
    - System stability report.
    - Scorecard and non scorecard characteristics analysis.
    - Score distributions of approves/customers report.

- Generate statistics for acceptance/override decisions.
    - Final score report
    - Override report

The following portfolio management reports should be utilised:

- To monitor the risk performance of accounts, estimate future loss rate and to evaluate bad rate predictions and manage expectations the following reports are essential.
    - Delinquency report.
    - Vintage analysis.
    - Delinquency migration report.
    - Roll rate across time report.

- To understand where losses are coming from and to take appropriate action in time the sources of delinquency must be monitored by using the following reports.
    - Delinquency report by region and other segments.
    - Marketing campaigns and competitive analysis.

It is important that the business reasons for changes in profiles and performances must be understood and explained. Merely looking at statistics has no value, to be able to make informed, risk adjusted decisions one must be able to explain why things have happened.

5.5. Conclusion

All providers of credit in South Africa are facing a changing paradigm due to their relevant credit laws being replaced with the NCA. Many existing practices and fee structures are outlawed by the new act and subsequently lenders will have to find new mechanisms to reduce their risk.

Credit scoring is an important risk reduction tool that has not been used to full effect by South African credit providers. According to Wendel and Harvey (2006: 5) two of the reasons for this were the limited availability of timely, accurate, and reliable data from credit bureaus and the reluctance of institutions to share client information. The NCA has now laid the foundation for effective credit scoring with the introduction of a compulsory national credit register.

The use of scorecards will allow lenders to reduce the costs associated with originating loans while at the same time improving the performance of their loan portfolios. The impact of these benefits will be an overall increase in the amount of credit available which will likely result in an increase in employment and growth (Wendel & Harvey, 2006: 5).

The scorecard which was developed in this dissertation will not be useful to other credit providers because their client demographics will be different. The value of this document therefore does not lie in the actual scorecard but in the example of how to go about developing such a scorecard.

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