APPLICATION OF MULTIPLE DISCRIMINANT ANALYSIS CREDIT SCORING MODEL, FOR CREDIT CARD CONSUMERS – THE CASE OF BARCLAYCARD KENYA

By

Mbijiwe, Jeremiah Muthomi

D61/P/8446/01

A MANAGEMENT RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT FOR THE REQUIREMENTS OF THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION, FACULTY OF COMMERCE, UNIVERSITY OF NAIROBI

JANUARY, 2005

DECLARATION

This is my original work and has not been submitted for a degree in any other university.

Signed ....

MBIJIWE JEREMIAH MUTHOMI

Date 18/10/2005 ....

This project has been submitted for examination with my approval as the University Supervisor.

Signed ....

LUTHER OTIENO

Lecturer, Department of Accounting

Faculty of Commerce

University of Nairobi

Date 21.10.2005 ....

Dedication

This project is dedicated to my Supervisor – Luther Otieno, family members and colleagues in MBA, all to whom I accord great honour, and respect.

ACKNOWLEDGEMENTS

The success of this study is a result of substantial encouragement, contribution, and support from several people to whom I highly feel indebted.

I wish to express particular gratitude to my supervisor, Luther Otieno who has tirelessly sacrificed his time and effort to provide me with invaluable guidance, advice, and constructive criticisms that significantly contributed to the successful completion of this work

Special thanks go to the entire staff of the Departments of Business Administration and Accounting, Faculty of Commerce, University of Nairobi for the academic nourishment. I am particularly grateful to co-ordinators of the MBA Program – Professor Aosa, Dr. Ogutu and Mr. J. Maalu for their successful co-ordination of the entire exercise.

TABLE OF CONTENTS

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

Ainco	....	Annual Income
AincoCl	....	Annual Income Classified
BBKCus	....	Barclays Bank of Kenya Customer
BouPay	....	Bounced Payments
BranchC	....	Branch Coded
CrLIM	....	Credit Limit
CrLIMCl	....	Credit Limit Classified
EAL	....	Excess Above Limit
FoCW	....	Frequency of Cash Withdrawals
FoLP	....	Frequency of Late Payment
GUARA	....	Guarantee
LoArreas	....	Loans in Arrears
LoArreaC	....	Loans in Arrears Coded
LOfficer	....	Loan Officer
Marital	....	Marital Status
MPR	....	Minimum Payment Rate
Nation	....	Nationality
NoCrH	....	Number of Credit cards Held
NoLOAN	....	Number of loans with Barclays Bank & other financial institutions
NoPiArr	....	Number of Payments in arrears
MDA	....	Multiple Discriminant Analysis
Para	....	Parastatal
SBU	....	Strategic Business Unit
K.Shs.	....	Kenya Shillings
BBK	....	Barclays Bank of Kenya
ANOVA	....	Analysis of Variance

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

ABSTRACT

Credit risk analysis is a process that allows financial institutions to minimize the amount of follow-up on late payment and loan default to be performed.

In order to reduce credit card default risk at Barclaycard Kenya and other credit card lenders in Kenya, this study investigates the suitability of multiple discriminant analysis model in differentiating between good and bad credit card holders.

Secondary data comprising of 100 good and 100 bad card holders was collected from existing customers application forms. The classification of an applicant as good or bad payer is based on characteristics and behavior of the person. Variables such as age, annual income and number of credit cards held were analyzed to create constituency by credit analysis.

Discriminant analysis technique is applied using statistical information related to the variables of the study to discriminate good credit risks from bad credit risks with an aim of application in the evaluation of new credit card applicants.

From the analysis, it emerged that discriminant analysis can identify groups differences existing in predetermined groups. However, some variables such as sex, nationality, town and annual income were found to be weak discriminants.

On overall, MDA technique is applied successfully therefore recommended for evaluation of new credit card applicants in Kenya.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background

Credit card lenders in affluent countries make massive numbers of small, short, unsecured micro loans at very low costs because they judge risk with statistical scoring variables (Hand and Henley, 1997; Mester, 1997; Lewis, 1990). The question that arises is whether lenders in poor countries rely on statistical scoring variables in their lending decisions, Vigano (1993).

In modern business transactions, credit cards are increasingly becoming an essential tool. A credit card offers a cardholder convenience, safety, higher purchasing power and a host of fringe benefits as most cards come wit h a number of privileges. This is over and above the basic benefits of serving in place of cash. From a business point of view, it is one of the most accepted, convenient and acceptable financial products. However, screening out credit risky customer is a crucial step in card application acceptance processes.

Credit card is a financial instrument that allows the cardholder to obtain funds at interest from a financial institution, at his/her own discretion, up to some limit (Edward Paul and Robert, 1997). The funds usually can be used only to make purchases, but sometimes they can be obtained as cash. If repaid within a certain period, usually within a month, the loan is interest free. If not, the loan may be carried for an indefinite period, always accruing new interest charges, by paying a minimum amount each month.

A credit card is distinguished from other financial instruments by the entitlement it gives borrowers to determine the size of the loan and the pace at which it is repaid, and as a flexible and readily available source of funds for consumption, may be used as a shield against the hardships of income loss, (Asubel, 1991).

Credit card plays a role in the strategic plans of many banks (Comptroller's HandBook, October 1996). A bank can be a card issuer, merchant acquirer, or an agent bank when it comes to credit card business. Issuing banks bear risk because they hold or sell credit card loans. A merchant bank enters into an agreement with the merchant to accept deposits generated by credit card transactions. It is possible that the merchant bank is exposed to some transaction risk arising from customer charge backs. An agent bank agrees to participate in another banks credit card program. This requires that the agent bank turnover its applications for credit card to the bank administering the program (Comptroller's HandBook, October 1996).

Barclaycard has been in the card business since 1990 and has a market share of over 60 percent of the credit cards in Kenya today (Barclaycard Issuing Presentation, September 2004). Barclaycard now issues the Visa brand, which is the most widely accepted in the world. The Kenyan business is the largest card business run by Barclays in Africa with over 40,000 cardholders. There are five other Barclaycard businesses in Africa including Botswana, Seychelles, Mauritius, Zambia and Zimbabwe with a combined total of 31,000 cardholders. (The Barclays globe Magazine issue; 21-September; 2003)

Table 1 : Competitor Products

Credit Card Issuer	Products Offered	Joining Fees KSH(000)	No. Of Cards (Estimate)	Requirements	Extra Features
KCB	Classic card Gold Card	Classic – 2K Gold – 3K Annual Classic – 2.5K Gold – 3.3K	10,000	1 month pay slip 3 months statements	Gold -Insurance -VIP treatment first class lounge JKIA
CBA	Classic Card Gold Card Business Card Visa Electron	Classic – 3.5K Gold – None Business – 10K (1- 5) cards Annual Classic –2.5 Business – 2.5K Gold – 2.5K of limit	4,500	1 month pay slip 3 months statements	Gold -Free entry JKIA 1st class lounge -Free entry Ngong Race course -Travel insurance -Intl emergency -No joining fee -buyers protection plan
Co-operative Bank	Local Classic International Classic Gold Visa	Local Classic – 3K International – 5k Gold Visa – none Annual Classic – 3K International–3.5K Gold – 2.5K	6,000	1 month pay slip 3mths statements 35K net salary	None
Barclays Bank	Visa Classic Prestige Visa Visa Gold Manchester United Company Barclaycard	Visa Classic – 3.5K International – 5k Visa Gold- 6K Company card- 4K Classic – 3K	40,000	2 month pay slip 3mths statements	-Free entry Ngong Race course -No joining fee

Source : Barclaycard Issuing Presentation –September 2004

Largely though, most people go for credit cards because they are easy to carry around as compared to cash, without understanding the cost implication. With plastic money in the pocket, one is able to transact business conveniently in practically any part of the world.

That one is able to get cash advances is perhaps the most attractive of the many advantages associated with credit cards. This eliminates the need to go to the bank as customers simply get the cash they need from various outlets.

In an effort to boost profits, credit card companies are using more aggressive marketing schemes to lure consumers. Credit card offers often begin with introductory letters by telling consumers that they are special, "Your excellent credit has earned you the best card we've ever offered." Credit card offers are meant to make consumers feel like they are part of an elite group of people. For example, American Express tells consumers, "As the membership criteria at American Express are becoming increasingly stringent, the Gold Card is becoming even more difficult to acquire. You, however, have demonstrated exceptional financial responsibility. For this reason, you have been selected for Approved Membership for the Gold Card."

Such marketing tactics are used to smooth talk consumers and make them feel part of a prestigious group of successful people who, because of their "good credit," now have an opportunity to acquire additional credit. Furthermore, Barclaycard has made credit cards easily accessible. Anyone earning a minimum a gross income of KShs. 20,000 per month and aged 18 and above can get one. You also do not have to bank with Barclays Bank to qualify; you only need to have an operational bank account. To ensure that many customers enjoy the benefits of Barclaycard, the joining criteria have been relaxed.

In most cases, the aggressive marketing is not accompanied with appropriate credit risk assessment leading to high delinquency and default rates. As a result, concentration of credit risks either product or sector specific causes problems for the lending institutions. The litany of troubles affecting the financial sector today is marginal lending or over extension of credit coupled with relaxed risk assessment. This results into losses in terms of bad debts that get pronounced during an economic downturn.

The tentative observation is that this sector has not establish itself as a growing and advanced, rather it has remained weak, narrow, and inefficient, with almost some credit firms or departments undergoing liquidation or just surviving (Bird J. et al 1997) The major problem facing suppliers of credit card is default by beneficiaries of this service (clients). This problem is traced to credit card application assessment. In which case it becomes necessary to introduce statistical credit rating that helps group current and potential credit card consumers into good and bad. A model suggested as useful for such a purpose is Multiple Discriminant Analysis Technique (DMA). Furthermore, the interest rate to be borne by credit card holder can be influenced by ratings assigned by the lending officer.

Multiple Discriminant analysis technique (MDA) is the study of differences between two or more groups, Orgler (1975). MDA has a wide number of uses in financial analysis, Foster (1986). It identifies the key variables that contribute to the most discrimination among groups.

This study will therefore contribute and add to existing knowledge on the importance of credit risk assessment for credit card applications as a prerequisite for profitability and adequate returns to shareholders of this SBU of Barclays Bank.

1.2. Research Problem

At Barclaycard, upon meeting the minimum joining criteria, credit decisions currently are based on credit reports, personal histories and judgment of the lending managers. This assessment criterion can be considered as impractical in a modern lending environment and therefore responsible for the rising delinquency levels to the tune of 25% within this business for the following reasons.

- A Judgement decision would not necessarily be made the same way by different lending officers or even by the same officer on different occasions. This is because it is made on emotional, intellectual and personal experience basis.

- It is impossible to make objective individual decisions on thousands of loan applicants without having a large body of experiences and experienced decision makers on hand.

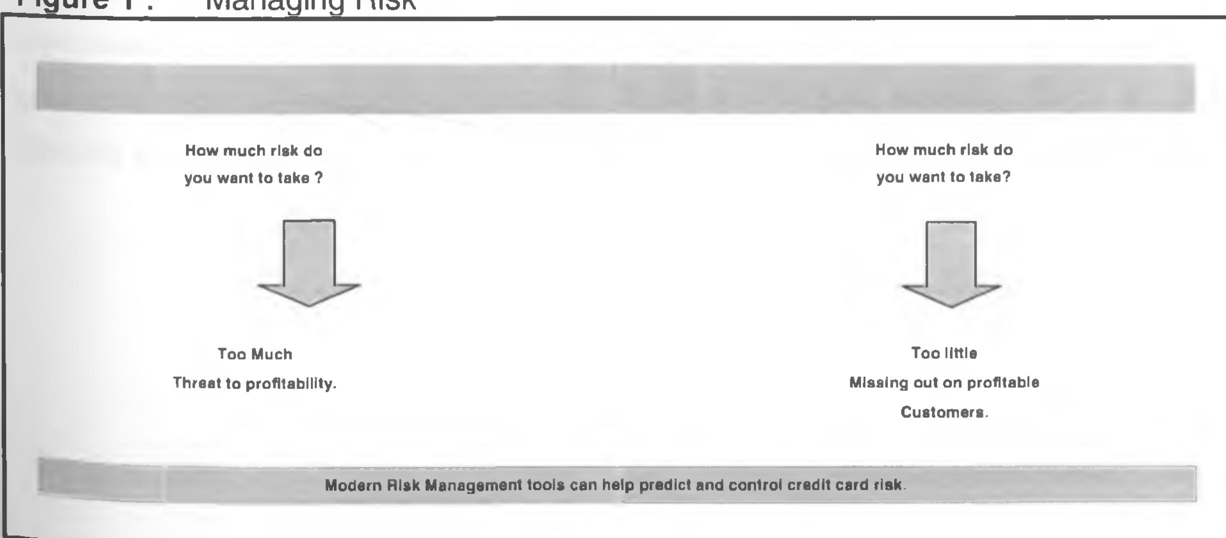
- Judgmental lending alone without some form of credit scoring is generally impracticable in a high volume consumer loan environment.

Due to the above limitations, a credit scoring system will seek to eliminate the judgment of the credit decision maker from the credit process.

Some banks have found they have been able to extend more loans under credit scoring than under their judgmental credit approval systems without increasing their default rates. Credit scoring may also encourage more lending because it gives banks a tool for more accurately pricing risk (Asch, 1995)

The task of screening out credit risky customer is a crucial step in card application acceptance processes. Lenders who are too strict will loose business while those who are too less strict will experience bad debts that might push them out of business.

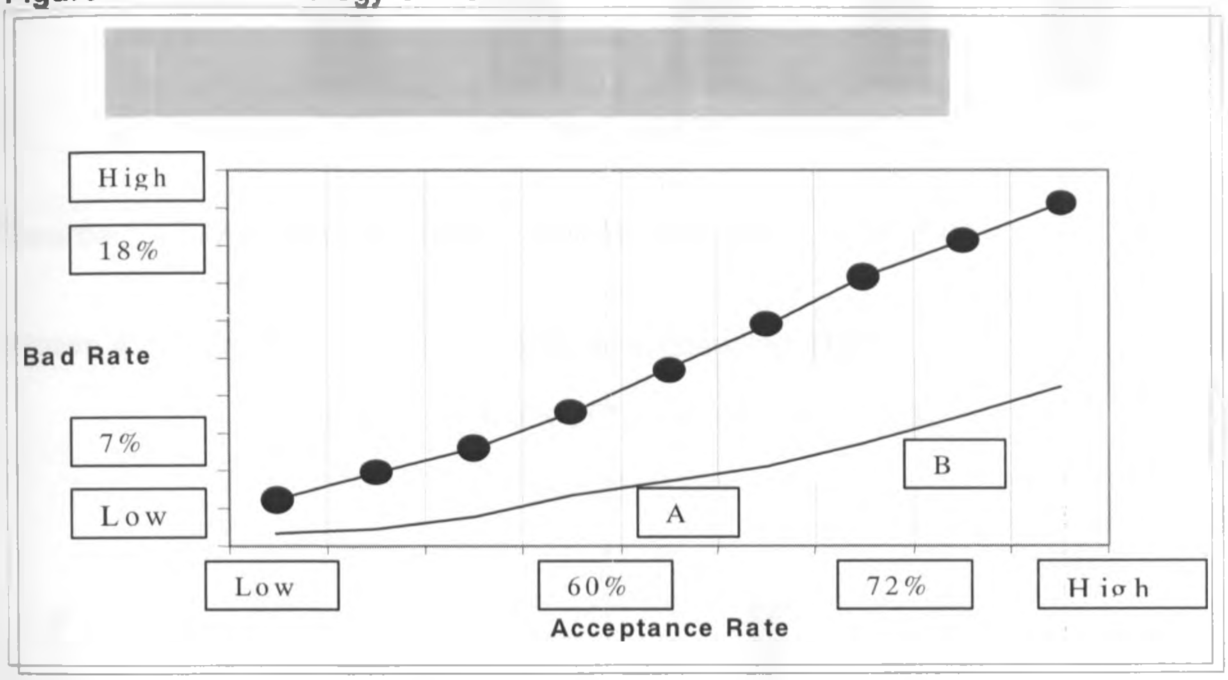
Figure 1 : Managing Risk



Source : (Visa Business School Training Hand Book, June 2000)

The dynamics of today's credit card market make it necessary for the successful issuing bank to manage every aspect of the lending process. In the past, it is likely that success may just have happened, but with today's strong competition from other issuers, including non-banks, and rapidly changing technologies, each and every step in lending function is crucial to maximizing profits, (Comptroller's HandBook, October 1996).

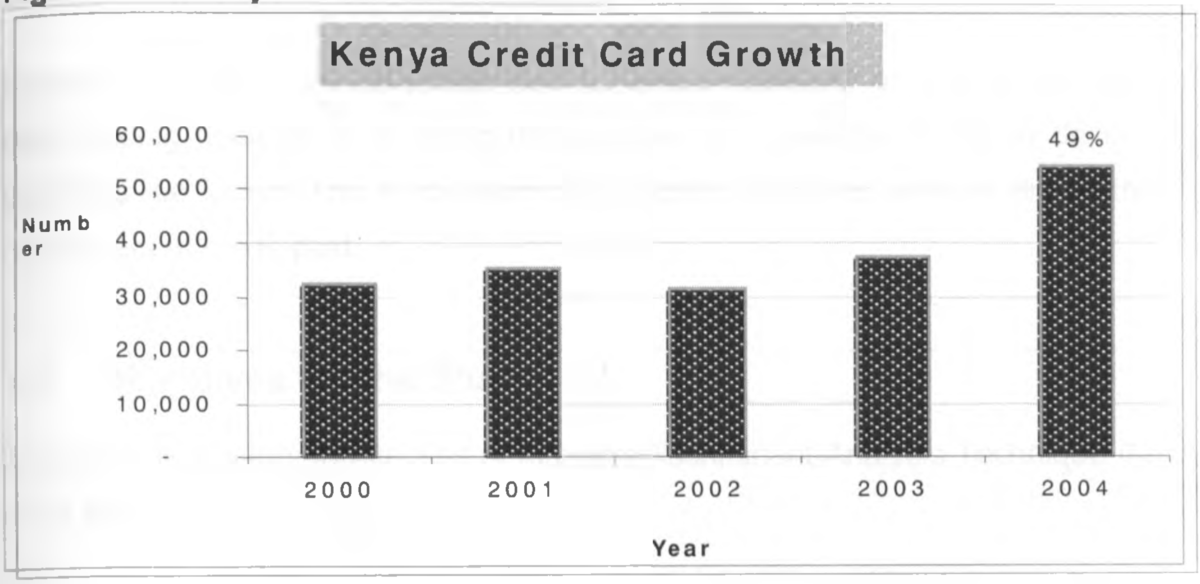
Figure 2 : Risk Strategy Curve



Source : Visa Business School Training Hand Book, June 2000

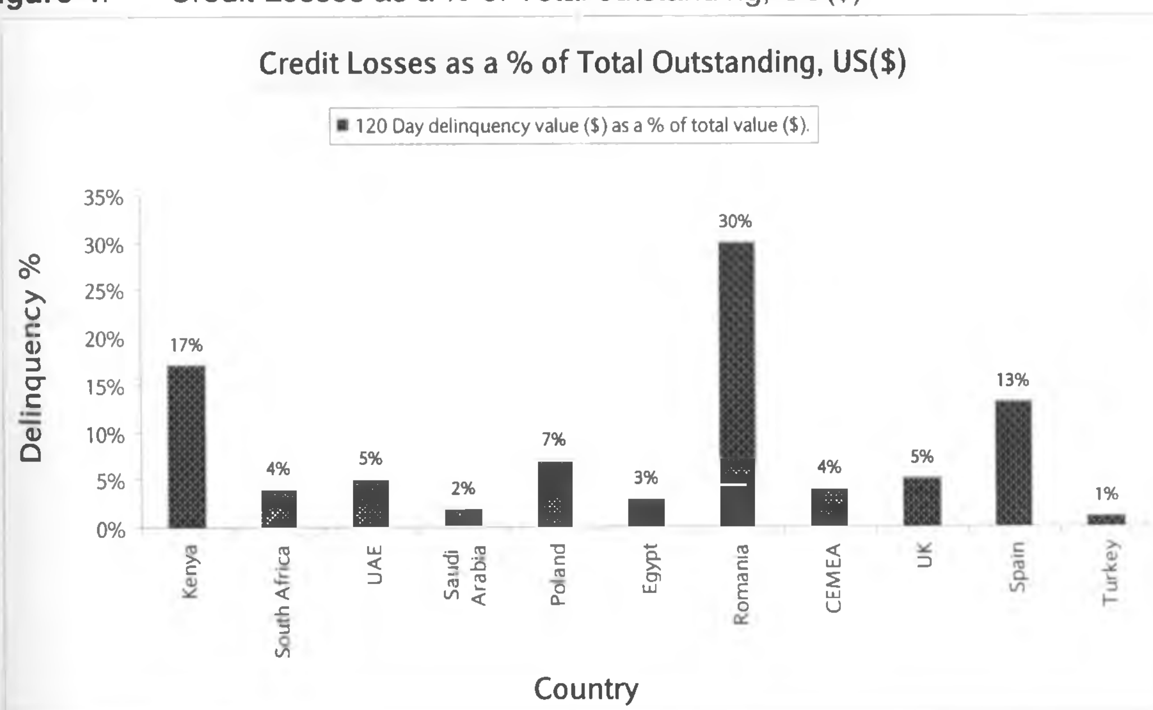
In Kenya, the exploratory observation is that the card business has grown dramatically as shown below, but remains weak, narrow, and inefficient, with some credit firms or departments undergoing liquidation or just surviving such as the Dinners Card company, (Visa Business School Training Hand Book, June 2000).

Figure 3 : Kenya Credit Card Growth



Source : (Visa Business School Training Hand Book, June 2000

Figure 4: Credit Losses as a % of Total outstanding, US($)



Source : Visa Business School Training Hand Book, June 2000

The phenomenon is forcing credit card suppliers to develop statistically based credit scoring models. In USA, the Equal Credit Opportunity Act specifies that lenders can employ credit-scoring techniques that are demonstrably statistically sound and empirically derived (Hsia 1978). A model widely suggested as useful in evaluating borrowers is Multiple Discriminant Analysis Technique (MDA), Altman et al (1981).

However, it is not empirically clear how far lenders can rely on this model, MDA, in their lending decision or in rating their current and potential clients in developing countries like Kenya. This study attempts to identify variables useful in discriminating consumers of credit card.

1.3 Objectives Of The Study

To establish the appropriateness of Multiple Discriminant Analysis Technique (MDA) in an actual lending situation.

1.4 Justification Of The Study

The various interest groups that might find this study useful include:

i. Commercial Banks with Credit Card division and need to improve on their lending decisions.
ii. Credit Card Applicants who will be able to know exactly the information requirements of Credit Card Issuers.
iii. Regulators whose interest is to minimize credit card failure.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

The diagrammatic growth in credit card programmes coupled with increasing concern for risk has generated considerable interest on the part of credit suppliers in developing statistically based credit scoring models. The objective of the study is to establish whether multiple discriminant analysis technique can be used to manage the issue of credit cards.

Schreiner (1999) observes that scoring models draw on observable objective personal traits to compare a potential borrower with past borrowers. The share of similar past borrowers who were "bad" in some sense is an estimate of likelihood that a potential borrower will also turn out to be bad. However, scoring may help lenders to judge risk, but are not meant to replace human factor in lending decisions.

2.2 Credit Card Risk

As consumer lenders broaden their marketing efforts in search of new borrowing, they also have altered the risk profiles of what were once relatively static portfolios. The growth in sub-prime lending, specifically the introduction of credit cards, has added new dynamic to many portfolios and poses challenges to risk mangers. For example, in the USA, while the industry has so far managed the risk environment reasonably well, the spike in the personal bankruptcies in 1996 –1998 periods caught many in the credit card industry off-guard. This along with more recently publicized difficulties experienced by several large sub-prime lenders, has provided additional evidence of increased risk. This has heightened awareness of the need for more sophisticated retail credit risk management tools and technologies.

One of the first to examine the problem of formulating an optimal credit granting policy was Geer [1967a] who proposed two models. One was designed to determine the optimal number of credit applicants to accept by maximizing "credit-related profits" which were a function of the present value of the profits from the current period credit sales, the present value of future profits from applicants granted credit in the current period, and the present value of profits from cash sales in both the current and future period. The second model also determined the optimal number of loans to market but included considerations of the opportunity costs of not granting loans to all applicants. Since this second model is formulated to differ from the first by only a constant it is not surprising that Geer finds that the optimal number of loans is the same with either model. This study aims to establish whether results obtained from using multiple discriminat analysis technique would be significantly different from Geers findings.

2.3 Credit Scoring

Since the mid and late 1960s credit scoring and related loan review, procedures have been utilized with increasing frequency by financial institutions and other creditors. Chandler and Coffman [1977], for example report that credit scoring systems are in wide use today. However, given the proprietary nature of these systems precious little is known about the specific content of the models. According to Chandler and Coffman there have been several credit scoring systems constructed by academics that have appeared in the journals. From their study, if these are representative of the types of systems being employed in industry, it would appear that a number of these systems could be expected to suffer from methodological and statistical problems that may have significant implications for the hundreds employing the models.

The credit card scoring problem is a particular case of a consumer lending techniques (Thomas, 2000). Scoring models are divided into two types: (1) models or techniques helping creditors to decide whether or not to grant credit to consumer who apply for credit, (2) behaviour scoring models help in deciding how to deal with existing consumers. This study focuses on the first type of scoring model.

In credit scoring, decision on extending credit to a client is based on the client's application for credit and an application obtained from a credit report agency. Information on previous applications and their performance is available. This is labeled information in sample information. A creditor uses sample information together with application information to make lending decision.

Thomas (2000) inform us that the objective of credit scoring is to find a rule that separates the "goods" from "bads", but the separation is at the highest level attainable, i.e. pick up the smallest possible percentage in the difference between "goods" and "bads". The notion of smallest possible percentage in the difference between implies that perfect classification is impossible. Perfect classification is impossible due to several reasons. There could be errors in the sample data. It is possible that some "good" application have exactly the same implication in data fields as bad application. In such a case, not enough information will be available to make a correct decision. Furthermore, Vapnik (1988) refer to the statistical learning theory which states that, for a model, the optimal prediction (i.e. out of sample classification with minimal classification) is achieved when the sample error is close to the out of sample error.

Leonard K. J. [1995] considers credit scoring as having the following merits:-

- It does not require any experience on the part of the credit decision maker.
- The credit standard can be adjusted easily as experience shows it to be too high or too low in terms of resulting delinquencies.
- The system can be adjusted for different credit programs, different products, different geographical areas, with due attention to compliance with legal requirements i.e., no discrimination.
- Computers can hide the weights in credit scoring systems and prevent doctoring of applications.
- Human credit decision makers can concentrate on those applications in the gray area requiring closer investigation.

However, it should be noted that even a good credit scoring technique will not always predict with certainty all individual cardholders performance, but it should give a fairly accurate prediction of the likelihood that a loan applicant with certain characteristics will default.

2.4 Multiple Discriminant Analysis (MDA)

Discriminate Analysis is the study of differences between two or more groups (Orlger, 1975). Discriminant Analysis distinguishes amongst groups and identifies group's differences existing and new observations into predetermined groups. It identifies the way variables that contribute the most to the discriminations among groups. The real benefit of predictive model may relate not to any superiority in the predictive power, but to the highly consistent objective and efficient manner in which such predictions are made, (Scott, 1978).

Credit scoring involves separating specific sub-groups in a population of objects. Such objects have significantly different risk characteristics, e.g. applicants for credit cards. Classification can be defined by a classification function that help in assigning to each object some categorical value called class number, e.g. one (1) for good and zero (0) for bad, (Damascos, 1977). A classification problem is reduced to evaluate a continuous utility function from some general class of functions. This function is used for separating objects belonging to different sets. Values for utility functions for objects from one class should be in the same range. The best utility function in some class is found minimizing the error of classification. Depending upon the class of utility function, it may be quite difficult problem from optimization point of view. However, if one is looking for a utility function, which is a linear combination of some other functions (possibly non-linear in indicator variables), it can be formulated as a linear programming problem. Mangasarian, Street and Wolberg (1995) used this approach for failure discriminant analysis with linear utility function (applications to breast cancer diagnosis).

2.5 Other Techniques Apart From MDA

Sophisticated scoring methods are employed for classifying and/or measuring delinquency and defiant probability for individual's retail credit internal economic capital models are less fully developed for retail.

At times, the MDA model results are relatively insensitive to a number of important assumptions. For example, MDA model is at times unable to satisfactorily predict marginal credit risk. This means that statistical techniques other than MDA might probably be more suitable such as regression analysis.

It is possible that the general nature of credit data is more consistent with using maximum likelihood techniques for estimating the parameters of a logit probability function, (Winginton, 1980). Other techniques that might be explored include regression analysis, factor analysis and multidimensional and contingency analysis. Each of these techniques can be useful in understanding the basis of the credit-granting process while human judgment and past experience is a must for a more complete analysis, (Winginton, 1980).

The operation research techniques on credit scores primarily include mathematical programming methods such as linear programming. In addition, several new non-parametric and artificial intelligence approaches were recently developed. They include ubiquitous neural networks, expert systems genetics algorithms and the nearest neighbourhood methods, (Thomas, 2000).

Many credit scoring approaches fail to provide clear explanations of reasons for favouring some objects and not favouring others. Capon (1982) considered this as the main draw back of many scoring algorithms. Furthermore, there are many implementation issues, which need to be addressed before using any credit scoring model. This includes: How to select a sample of previous applicants? How long should be the period of time for the sample set? What proportion of "goods" and "bads" should comprise of the sample.

Statistical approaches using linear scoring functions (Bayesian decision rule discrimination analysis and linear regression) became the most popular for classification problem. The Bayesian decision work especially well in the case when the distribution of "good" and 'bads" can be described by multi-variate normal distributions with a common covariance matrix; this reduces the problem to linear decision rule. However, if the covariances of these populations are different then, it leads to quadratic decision rule. Titterington (1992) position is that in many cases the quadratic scoring function appears to be less robust than the linear one.

2.6 Data Mining and Data Discovery

This project is focused on a numerical validation of the proposed algorithm. The aim is to investigate the impact of model flexibility as classification characteristics of the algorithm. Broadly speaking, the classification problem can be referred to as a problem of the data mining or knowledge data discovery. During the last 50 years a wide set of different methodologies was proposed for data discovery. Data mining techniques can be divided into five classes, Brandley, Fayyad, and Mangasarian (1991): predictive attribute based on other attributes in the data); clustering (grouping) similar data records into subjects); dependency modeling (modeling a joint probability function of the process); data summarization (finding of summaries of parts of data; and change or deviation detection (accounting for sequence information in data records).

2.7 Effects of individual traits

Lenders want to predict the probability of arrears, and they also want to know which traits influence that probability. This section discusses the influence of traits, according to Schreiner, M., (Oct.1999):

Experiences as a borrower

The proxy for experience is the number of previous loans and months since the first loan. We expect improvement as experience increases. The coefficients for experience are positive as risk increases, and negative as risk is decreased risk.

Number of previous loans

Looking at precisely estimated effects, the chance of costly arrears decreases with the number of past loans. For example, bad arrears are 5 percentage points less likely for an eighth-time borrower than for a first time borrower. Given normal evaluation, borrowers who have had more loans are at better risks at disbursement.

Months since the first loan

Experience in months since the first loan differs from experience as pervious loan because, for example, a borrower could get three one month loans or three one year loans. We expect the effects of time to be non-linear and to fade. For example, if the first loan is repaid on time, then the lender tends to press for bigger and better loans, whether or not borrowers are still as able to repay as for the first loan. As most time passes, however, the chances increase that something will happen to worsen risk.

Arrears in the most recent loan

Past arrears should predict future arrears well. Lenders cannot check records with a credit beaureaux, but they do know the repayment performance of their own borrowers. He measures past arrears as days in the longest spell and as number of spells. To avoid co linearity with the set of dummies for previous loans, the practice is to count first time borrowers as if they had no past arrears, and lump zero and one spell in a single dummy.

Length of spells

Common sense suggests that the effect would grow with the length of past arrears. Schreiner (1999) counts first time borrowers as having no arrears in their non-existent previous loan, but this does not explain the puzzle. Most likely, length of arrears picks up the effect of some omitted variable, or perhaps the data is in error. But the effect might be real; some arrears are due to shocks that are not the fault of the borrower, and perhaps the borrowers who have had some arrears but who worked to get back on track in just a few days are, on average, better risks than those who have not yet fallen into arrears but who might not be so quick to repay once they do.

Number of spells

The number of spells has a big, precise effect. This may reflects borrowers who make frequent installments but who are always a day or two late, not from negligence but because they wait to combine the trip to the branch with other errands. For them, the number of spells of arrears reveals little about the risk of long arrears.

Sex

The folk wisdom in finance is that women are at better risks than men are.

Amount disbursement

The effect of the level of the amount disbursed is precise but small. In Bolvia, in dollars as of the end of 1998, each $100 disbursed raised risk by 0.02 percentage points. A $100 decrease did decrease risk by 0.1 percentage points. It seems the lender successfully rations borrowers suspected as bad risks. The effect of the amount disbursed is small. Furthermore, the lender has little scope to affect arrears via loan size because the average loan is already small ($680) and because the average increases ($140) and have decreases ($125) are even smaller.

Guarantees

Perhaps only borrowers judged as very low risks in the normal evaluation could borrow without a guarantee. Changes in the guarantee do not affect risk.

Model detects risky branches better than simple measure of arrears. The branch effect matters because branch performance is susceptible to policy, for example through bonuses or training.

Loan officers

Most lenders base their normal evaluation on the subjective judgment of loan officers. Of course, officers differ in their ability to smell bad risks, and they may take time to learn the ropes and to sharpen their sixth sense.

Although loan officers learn to work smarter with time, the amount of work to do also grows as their portfolios also expand. In addition, the quality of new borrowers may degrade as officers mine the neighborhoods where they work deeper and deeper.

Beyond experience, loan officers differ in their ability to sense bad risks. Compared with "other" officers, we expect the safest officer to decreased risk, and the riskiest officer to increased risk. Loan officers are not interchangeable parts; lending rests on personal relationships, so the person who is an officer is important. This matters because lender policy probably has more influence over officers than over borrowers. Thus, decreased turn over in lending officers may decrease arrears.

Date of disbursement

To control for seasonal or one-shot changes in the market or lender policy, researchers include sets of dummies for the year and month of disbursement. Loans disbursed in the months before Christmas when business is heaviest are more risky.

In sum, risk depends on sex, sector, past arrears, the experience of the borrower and of the loan officer, and the specific loan officer and branch. Seasonality and changes in the policy and the market also matter. Even if a lender does not score individual borrowers, these results could help to guide adjustments to normal operations.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Research Design

Introduction

The central problem in this study is: How does a credit card organization decide which applications should be given a card and which ones should not? It has emerged that using historical and statistical techniques, MDA can be used to isolate the effects of various applicant characteristics on delinquencies and defaults. This is because the method produces a score that a credit card lending institution can use to rank its loan applicants or borrowers in terms risk.

The discriminant model uses knowledge of the traits of past and current credit card holder at the time of issue of credit card and of their subsequent repayment performance to infer future repayment risk of potential credit card applicants whose traits are known and who have passed the standard evaluation. The dichotomous dependent variable used in deriving the predictor coefficients, is unity (1) for credit cards that are not problematic and, zero (0) for credit cards that are problematic.

3.2 Research Hypothesis

The Research hypothesis to be tested is:

Null Hypothesis, H_o: "Discriminant Analysis does not identify group's differences existing in predetermined groups".

Alternate Hypothesis, H_1: "Discriminant Analysis identify group's differences existing in predetermined groups"

3.3 Population

The population of interest consists of credit card holders of all the card products issued by Barclaycard Kenya. The portfolio is internally divided into two categories, that is good and bad cardholders. These total up to 40,000 credit cardholders. This being approximately over 60% of the total card base in Kenya, a sample study carried out should be representative of the entire population.

3.4 Sample and Sampling Approaches

A cardholder at Barclaycard Kenya is regarded as BAD if the following features are evident in his credit history.

- 30 days or more payments in arrears;
- Frequent cash withdrawals;
- Bounced auto payments;
- >10% excess above the maximum credit limit;

Good cardholders make up about 75% of the total population/card book while the remaining 25% is comprised of bad cardholders.

A random sample of 200 credit card holders was selected from the population. This was stratified according to GOOD -100 cardholders and BAD – 100 cardholders, criteria.

For the purpose of this study, the classification of an applicant as good or bad payer is based on characteristics and behavior of the person. Various variables were considered: data from application form (such as occupation, income, location, time at present address, age of applicant, accommodation type, number of children etc.) and behavioral data of current and recent activities (e.g. credit history, average balance, payment of orders and making the new orders).

To eliminate dilution of results due to recently issued credit cards, a cut off period of 3 months prior to the time of this study was considered.

3.5 Data Type and Sources

Secondary data obtained from customers application forms was used to extract information on variables of the study. Behavioral data was obtained from the internal credit card monitoring and control IT software.

Table 2 : Variables Of The Study

Variables Of The Study		
Status	Good [1]	Bad [0]
Sex	Male [1]	Female [0]
Age	Years	
Employment	Private [1]	Public Sector [0]
City		
Nationality		
Annual income in KShs		
Bank Account of BBK	Yes [1]	No [0]
BBK or other bank		
No. of credit cards held		
Mode of payment auto pay	Yes [1]	No [0]
Mode of payment cash	Yes [1]	No [0]
Mode of payment cheque	Yes [1]	No [0]
Minimum payment rate e.g., 10%, 20%, 50%, 100% etc.,		
Credit limit in Shillings	KShs.	
Frequency of cash withdrawals within period under study		Number
Frequency of late payment	Number	
Excess above limit	KShs.	
Current balance vs. credit limit	Credit limit	Balance
Delinquency/No of payment in arrears	Number	
Bounced payments received	Number	

3.6 Data Analysis

The technique used should enable us answer the question: How does a credit card officer in a bank categorize some customers as good credit risk and some as bad credit risk?

In the literature review, discriminant analysis technique has been identified. The idea is to indicate those variables, from the variable list above, which are important for distinguishing among the groups and develop a rule, or specifically identify as Altman co-efficients, for predicting good or bad credit risks.

Researchers use discriminant analysis to classify observations into two or more groups if you have a sample with known groups. Discriminant analysis can also be used to investigate how variables contribute to group separation.

An observation is classified into a group if the squared distance (also called the Mahalanobis distance) of observation to the group centre (mean) is the minimum. An assumption is made that covariance matrices are equal for all groups. There is a unique part of the squared distance formula for each group and that is called the linear discriminant function for that group. For any observation, the group with the smallest squared distance has the largest linear discriminant function and the observation is then classified into this group.

Linear discriminant analysis has the property of symmetric squared distance: the linear discriminant function of group i evaluated with the mean of group j is equal to the linear discriminant function of group j evaluated with the mean of group i.

I have described the simplest case, no priors and equal covariance matrices. If you consider Mahalanobis distance a reasonable way to measure the distance of an observation to a group, then you do not need to make any assumptions about the underlying distribution of your data.

There is no assumption with quadratic discriminant analysis that the groups have equal covariance matrices. As with linear discriminant analysis, an observation is classified into the group that has the smallest squared distance. However, the squared distance does not simplify into a linear function, hence the name quadratic discriminant analysis.

Unlike linear distance, quadratic distance is not symmetric. In other words, the quadratic discriminant function of group i evaluated with the mean of group j is not equal to the quadratic discriminant function of group j evaluated with the mean of group i. On the results, quadratic distance is called the generalized squared distance. If the determinant of the sample group covariance matrix is less than one, the generalized squared distance can be negative.

Minitab and SPSS statistical packages offer both linear and quadratic discriminant analysis. With linear discriminant analysis, all groups are assumed to have the same covariance matrix. Quadratic discrimination does not make this assumption but its properties are not as well understood.

3.7 Tests Of Significance

The application of discriminant analysis is in fact not allowed if within- group covariance matrices are significantly different. The objective of the test is to examine whether there is a significant difference between centroid of group 0 and centroid of group 1.

We are confronted with several problems: not only the problem that the dispersion of the variable in the two groups can be different, but also the problem that the variables can be mutually correlated within groups and moreover, the problem that the dispersion of a variable within a groups can be unequal. In other words: the within groups covariance matrices are not necessarily diagonal (think of cigar standing upright) and not necessarily scalar (think of circles)

$$\text{EIGEN VALUE} = \frac{\text{Between Group SS}}{\text{Within Group SS}}$$

$$\text{CANONICAL CORRELATION} = \frac{\text{Between Group SS}}{\text{Total SS}}$$

Conical correlation is the measure of degree of association between the discriminant score and the group. In other words, conical correlation is the regular R^2 in the regression analysis table where the dependent variable is D the discriminant function and the independent variable is group.

Wilks' lambda is the ratio of within groups sum of squares to the total sum of squares. Lambda is one if all observed group means are equal, and it is close to zero if variation within groups is small relative to the total variation. That is large values of lambda indicate that group means are not different, while small values indicate that group means do appear to be different.

$$\text{Wilks' Lambda} = \frac{SSE}{SST}$$

The F values and their significance are the same as those calculated from a one-way analysis of variance with status as the grouping variable. Large values of F indicate that group means are different.

In discriminant, analysis the study employs a function very similar to the regression equation and it's called the *discriminant function*. In regression analysis weighted combination of predictor variables (independent variables is used to predict the response variable. While, in discriminant analysis a weighted combination of predictor variables are used to classify an object into one of the criterion variable groups.

The weighted combination of independent variables (sex to bounced payment) is formed and serves as an index. This index is the basis for comparing different cases. In general, the discriminant function is written as

$$D = .\,_0 + .\,_1X_1 + \cdots + .\,_pX_p$$

The co-efficients are chosen so that the values of the discriminant function differ as much as possible between groups. Therefore for the discriminant indices the ratio

$$\frac{\textbf{Sum of square between groups}}{\text{Sum of square within groups}}$$

is maximum. Any other linear combination of the variables will have a smaller ratio.

CHAPTER FOUR

4.0 DATA ANALYSIS

4.1 : Introduction

The objective of this study is to discriminate between good and bad credit card holders . Twenty-one (21) discriminating variables were distinguished. These were marital status, sex, age, employer, town, nationality, average annual income, whether BBK account holder, number of credit cards held, number of loans, minimum payment rate, credit limit, frequency of cash withdrawals, frequency of late payments, excess above limit number of payments in arrears , bounced payments, whether there are guarantees, Branch, Loan Officer and length of longest spell of arrears (Days).

These twenty-one variables taken together were examined for their capability to discriminate significantly between the two kinds of credit card holders bad (O) and good (1). We name a prior classification of groups based on the records available. Such a classification is the subject of the explanation. It represents the (dichotomous) dependent variable with categories of bad (O) and good (1).

The discriminating variables are considered as causal factors in a multi-causal model. We search for a linear combination of the discriminating variable (21 of them) in such a way that the two groups (bad [0] and good [1] credit card holders) are maximally distinguished. The raw data used in the analysis and deriving the coefficients of discriminating variables are in appendix 1.

4.2 : Summary Group Statistics

There were 100 bad credit card holders and 99 valid good credit card holders. The married groups dominated good credit card holders (with a score of 0.96) compared to bad credit card holders who have unmarried as a majority. Nationality and town appear not to matter. This is explained by the fact that majority of card holders [good and bad] at Barclaycard are Kenyans living in Nairobi, hence the means of good and bad customers do not significantly differ. Factors such as number of payments in arrears [NOPIARR] bounced payments, [BOUPAY] and Loans in arrears [LOARRS] recorded wide disparities between the means of good versus bad borrowers. It follows that these are good predictor variables of default risk. The results are contained in Table 3. One case had one missing discriminating variable.

Table 3 : Group Statistics

	CLASS 0- Bad Credit Card Holder			CLASS 1- Good Credit Card Holder			All Credit Card Holders Good & Bad		
Dvar	Mean	Std. Dev	Valid N	Mean	Std. Dev	Valid N	Mean	Std. Dev	Valid N
MARITAL	0.69	0.46	100	0.96	0.20	99	0.82	0.38	199
SEX	0.92	0.27	100	0.87	0.34	99	0.89	0.31	199
AGE	36	5.77	100	38	6.44	99	37.33	6.16	199
EMPCLCD	3.18	2.18	100	2.03	2.15	99	2.61	2.24	199
TOWN	0.78	0.42	100	0.77	0.42	99	0.77	0.42	199
NATION	0.99	0.10	100	0.99	0.10	99	0.99	0.10	199
AINCOCL	2.63	1.04	100	2.55	0.96	99	2.59	1.00	199
BBKCUS	0.36	0.48	100	0.76	0.43	99	0.56	0.50	199
NOCRH	1.91	0.91	100	0.58	0.86	99	1.25	1.11	199
NOLOAN	1.93	1.13	100	1.21	0.59	99	1.57	0.97	199
MPR	0.48	0.31	100	0.26	0.26	99	0.37	0.31	199
CRLIMCL	2.36	1.26	100	2.71	1.19	99	2.53	1.23	199
FOCW	5.43	3.43	100	2.24	1.74	99	3.84	3.15	199
FOLP	6.02	2.35	100	0.14	0.47	99	3.10	3.40	199
BAL	0.53	0.21	100	0.00	0.02	99	0.27	0.30	199
NOPIARR	4.83	1.85	100	0.00	0.00	99	2.43	2.75	199
BOUPAY	4.21	1.42	100	0.07	0.29	99	2.15	2.31	199
QUARA	0.02	0.14	100	0.04	0.20	99	0.03	0.17	199
BRANCHC	10.89	7.22	100	13.35	9.05	99	12.12	8.25	199
LOARREAS	141.24	55.44	100	0.97	3.99	99	71.46	80.55	199
LOARREAC	8.51	1.48	100	1.28	0.83	99	4.91	3.82	199

4.3 Test of Equality of Groups Means

Test of equality of group means measure each independent variables' potential to discriminate before the model is created (see Table 4 & 5). Each test displays the result of one-way Analysis of Variance (ANOVA) from the independent variables using grouping variable as the factors. If the significance value is greater than 0.10, the variable probably would not contribute to the model. According to result obtained in Table 4, the variables that are not significant are sex (0.241) town (0.836), nationality (0.944) annual income (0.533) and guarantee (0.403). Wilk's lambda is another measure of a variable's potential. A small value of Wilk's lambda for a variable indicates the variable is better at discriminating between groups. Tables 4 and 5, show that variables with the lowest values of Wilk's lambda include loan arrears, 0.99, bounces payments (0.195) number of payments in arrears (NOP ARR) – 0.227, excess above limit (EAL) 0.249 and frequency of late payment (FOLP) 0.249.

A test of equality of group means i.e. comparing the differences in the variable means of good and bad credit card holders is done to select variables with a potential to discriminate. The results are in Tables 4 and 5. This is basically a test for group equality of means for the independent variables for example, for the variable marital in Table 4. In Table 4 are results for all independent variables whereas in Table 5 we only present variables used to derive this study's discriminating function.

Table 4 : Tests of Equality of Group Means - Bad and Good Credit Card Holders

	Wilks' Lambda	F	df1	df2	Sig.
MARITAL	0.875	28.23	1	197	0.000
SEX	0.993	1.38	1	197	0.241
AGE	0.977	4.57	1	197	0.034
EMPCLCD	0.934	13.99	1	197	0.000
TOWN	1.000	0.04	1	197	0.836
NATION	1.000	0.00	1	197	0.994
AINCOCL	0.998	0.35	1	197	0.553
BBKCUS	0.840	37.58	1	197	0.000
NOCRH	0.635	113.02	1	197	0.000
NOLOAN	0.863	31.36	1	197	0.000
MPR	0.871	29.19	1	197	0.000
CRLIMCL	0.980	3.99	1	197	0.047
FOCW	0.743	68.08	1	197	0.000
FOLP	0.249	594.20	1	197	0.000
EAL	0.249	593.25	1	197	0.000
NOPIARR	0.227	672.24	1	197	0.000
BOUPAY	0.195	810.83	1	197	0.000
GUARA	0.996	0.70	1	197	0.403
BRANCHC	0.978	4.51	1	197	0.035
LOARREAS	0.238	630.45	1	197	0.000
LOARREAC	0.099	1795.69	1	197	0.000

Table 5 : Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
MARITAL	0.875	28.235	1	197	0.000
AGE	0.977	4.57	1	197	0.034
EMPCLCD	0.934	13.99	1	197	0.000
NOCRH	0.635	113.02	1	197	0.000
NOLOAN	0.863	31.36	1	197	0.000
MPR	0.871	29.19	1	197	0.000
CRLIMCL	0.980	3.99	1	197	0.047
FOCW	0.743	68.08	1	197	0.000
FOLP	0.249	594.20	1	197	0.000
EAL	0.249	593.25	1	197	0.000
NOPIARR	0.227	672.24	1	197	0.000
BOUPAY	0.195	810.83	1	197	0.000
BRANCHC	0.978	4.51	1	197	0.035
LOARREAC	0.099	1795.69	1	197	0.000

In general the larger the difference between the means of the two groups relative to the within group variability the better the discriminating function. The significance score is 0.000 and below the $\propto$of 0.05 – hence we conclude that, with a prior probability of 95 percent, the mean marital of good and bad credit card holders are significantly different. However, for the variables sex, town, nationality, annual income and guarantee the significance scores are above the critical $\propto$of 0.05 and we conclude that, for these factors accurate prediction of an individuals' loan performance cannot be determined with certainty. Town and nationality have no influence because 99% of applicants comprising the sample were of Kenyan nationality while a majority of them come from Nairobi. Since majority of customers apply for credit limits between K.shs. 20,000 to 100,000, very limited number of card holders in the sample, provided a guarantee as a minimum for borrowing above K.shs. 200,000, hence the lack of influence on default risk determination.

Annual income was considered independent of net monthly salary commitments, thus the weak disciminant effect on this variable.

4.4 Discriminant Analysis

As mentioned earlier discriminant analysis attempts to find linear combinations of those variables that best separate the groups of cases – groups being bad and good credit card holders and the cases being 100 in each group. The procedures are called discrimination function.

Function 1 : Standardized Canonical

Discriminant Function Coefficients	
Variable	Coefficients
MARITAL	-0.0782
AGE	0.0400
EMPCLCD	-0.0565
NOCRH	0.2077
NOLOAN	0.1458
MPR	0.0423
CRLIMCL	-0.1331
FOCW	-0.4034
FOLP	0.4229
EAL	0.3643
NOPIARR	-0.3048
BOUPAY	0.0360
BRANCHC	-0.0193
LOARREAC	0.9813

Function 2 : Classification Function Coefficients

Variable	Bad	Good
	0	1
MARITAL	-2.853	-1.173
AGE	1.118	1.068
EMPCLCD	0.061	0.262
NOCRH	2.506	0.701
NOLOAN	3.070	1.830
MPR	1.554	0.415
CRLIMCL	0.389	1.225
FOCW	-0.684	0.454
FOLP	1.781	-0.131
EAL	12.799	-5.704
NOPIARR	-2.560	-0.776
BOUPAY	-0.650	-0.920
BRANCHC	0.233	0.251
LOARREAC	8.488	2.215
(Constant)	-63.054	-27.406
Fisher's linear discriminant functions		

The first function separates the groups as much as possible. The second function is both uncorrelated with first function and provides as much further separation as possible. The procedure is continued until reaching the number of functions as determined by the number of practitioners and categories on the dependent variable.

Table 7b : Classification Function Coefficients

VARIABLE	CLASS	
	0	1
MARITAL	-2.853	-1.173
AGE	1.118	1.068
EMPCLCD	0.061	0.262
NOCRH	2.506	0.701
NOLOAN	3.070	1.830
MPR	1.554	0.415
CRLIMCL	0.389	1.225
FOCW	-0.684	0.454
FOLP	1.781	-0.131
EAL	12.799	-5.704
NOPIARR	-2.560	-0.776
BOUPAY	-0.650	-0.920
BRANCHC	0.233	0.251
LOARREAC	8.488	2.215
(Constant)	-63.054	-27.406
Fisher's linear discriminant functions		

There is a separate function for each group. See function 2 in table 7b above. For example the coefficient for marital is larger for the good credit card holders, which shows, that married card holders are less likely to default. The employer is equally an important factor when discriminating credit card holders. The variables with the highest discriminating coefficients are loans in arrears (8.488 vs. 2.215), excess above limit (12.799 vs. -5.704), Number of loans (3.070 vs. 1.830), and number of credit cards held (2.506 vs. 0.701). You notice the difference in coefficients of variables such as age (1.118 vs. 1.06/8) branch (0.233 vs. 0.251) is marginal and not useful in separating bad and good credit card holders. Frequency of late payment is just as an important factor to be considered (1.781 vs. -0.131).

4.5 Correlation

Two variables are correlated if a change in the value of one signifies a change in the other. The within group correlation matrix shows correlation between the predictors (see Table 6).

Table 6 : Within Group Correlation Matrix

	MARITAL	SEX	AGE	EMPCLCD	TOWN	NATION	AINCOCL	BBKCUS	NOCRH	NOLOAN	MPR	CRLIMCL	FOCW	FOLP	EAL	NOPIARR	BOUPAY	GUARA	BRANCHC	LOARREAS	LOARREAC
MARITAL	1.000	0.138	0.464	0.031	-0.059	-0.050	0.010	0.099	-0.008	0.042	0.063	0.046	-0.123	0.027	-0.127	-0.068	-0.072	0.065	0.009	-0.107	-0.071
SEX	0.138	1.000	0.269	0.022	-0.148	-0.035	0.019	-0.010	-0.004	-0.015	-0.024	0.068	-0.051	-0.078	-0.033	-0.017	-0.039	-0.030	0.058	-0.042	-0.086
AGE	0.464	0.269	1.000	-0.020	-0.142	-0.003	0.021	0.046	0.029	-0.067	0.146	0.082	-0.043	0.065	-0.093	-0.065	-0.018	0.059	-0.011	-0.069	-0.067
EMPCLCD	0.031	0.022	-0.020	1.000	0.098	-0.042	0.072	0.088	0.087	0.077	0.076	0.117	0.141	0.095	0.123	0.050	0.144	0.034	0.015	0.103	0.095
TOWN	-0.059	-0.148	-0.142	0.098	1.000	0.066	0.065	-0.123	0.058	-0.036	0.053	0.199	0.142	-0.023	0.062	0.058	0.038	0.096	-0.235	0.134	0.098
NATION	-0.050	-0.035	-0.003	-0.042	0.066	1.000	-0.092	0.013	0.028	0.064	-0.101	-0.039	-0.043	0.094	0.016	0.032	0.014	0.018	-0.011	0.029	0.033
AINCOCL	0.010	0.019	0.021	0.072	0.065	-0.092	1.000	0.027	-0.002	0.050	0.015	0.149	0.016	-0.041	0.020	-0.020	0.005	0.105	-0.078	0.014	0.032
BBKCUS	0.099	-0.010	0.046	0.088	-0.123	0.013	0.027	1.000	-0.074	0.118	-0.195	-0.036	-0.052	-0.054	-0.004	0.018	-0.053	0.016	0.001	-0.002	-0.015
NOCRH	-0.008	-0.004	0.029	0.087	0.058	0.028	-0.002	-0.074	1.000	0.033	-0.022	0.079	0.110	-0.003	0.136	0.050	0.139	-0.038	-0.110	-0.007	0.002
NOLOAN	0.042	0.015	-0.067	0.077	-0.036	0.064	0.050	0.118	0.033	1.000	-0.133	0.063	0.210	-0.049	0.293	0.042	0.077	0.010	0.066	0.028	-0.016
MPR	0.063	-0.024	0.146	0.076	0.053	-0.101	0.015	-0.195	-0.022	-0.133	1.000	0.113	0.011	0.103	0.023	-0.056	0.185	0.064	-0.029	0.006	0.028
CRLIMCL	0.046	0.068	0.082	0.117	0.199	-0.039	0.149	-0.036	0.079	0.063	0.113	1.000	0.072	0.028	0.022	-0.012	0.059	0.204	-0.127	0.033	0.075
FOCW	-0.123	-0.051	-0.043	0.141	0.142	-0.043	0.016	-0.052	0.110	0.210	0.011	0.072	1.000	0.139	0.675	0.402	0.422	0.045	-0.107	0.383	0.318
FOLP	0.027	-0.078	0.065	0.095	-0.023	0.094	-0.041	-0.054	-0.003	-0.049	0.103	0.028	0.139	1.000	0.144	0.014	0.267	-0.045	-0.005	0.033	0.037
EAL	-0.127	-0.033	-0.093	0.123	0.062	0.016	0.020	-0.004	0.136	0.293	0.023	0.022	0.675	0.144	1.000	0.479	0.512	0.017	-0.016	0.439	0.362
NOPIARR	-0.068	-0.017	-0.065	0.050	0.058	0.032	-0.020	0.018	0.050	0.042	-0.056	-0.012	0.402	0.014	0.479	1.000	0.537	-0.060	-0.114	0.887	0.741
BOUPAY	-0.072	-0.039	-0.018	0.144	0.038	0.014	0.005	-0.053	0.139	0.077	0.185	0.059	0.422	0.267	0.512	0.537	1.000	-0.107	-0.047	0.548	0.495
GUARA	0.065	-0.030	0.059	0.034	0.096	0.018	0.105	0.016	-0.038	0.010	0.064	0.204	0.045	-0.045	0.017	-0.060	-0.107	1.000	-0.033	-0.057	-0.078
BRANCHC	0.009	0.058	-0.011	0.015	-0.235	-0.011	-0.078	0.001	-0.110	0.066	-0.029	-0.127	-0.107	-0.005	-0.016	-0.114	-0.047	-0.033	1.000	-0.092	-0.090
LOARREAS	-0.107	-0.042	-0.069	0.103	0.134	0.029	0.014	-0.002	-0.007	0.028	0.006	0.033	0.383	0.033	0.439	0.887	0.548	-0.057	-0.092	1.000	0.877
LOARREAC	-0.071	-0.086	-0.067	0.095	0.098	0.033	0.032	-0.015	0.002	-0.016	0.028	0.075	0.318	0.037	0.362	0.741	0.495	-0.078	-0.090	0.877	1.000

a The covariance matrix has 197 degrees of freedom.

Age and sex are positively correlated (0.269) and age and marital status (0.464). The credit card holders who have bounced payments seem to vary from employer to employer or on whom their employer is. It appears the excess above limit (EAL) too, varies with who the employer is. The same applies to credit limit. Minimum pay rate depends on whether one is BBK customer or not the correlation is (-0.195). Excess above limit EAL is positively correlated to no of credit cards held (NOCRH) NOCR is also positively correlated to bounce payments i.e. those who do not honour their payments tend to hold more than one credit card i.e. they have options to resort to whenever they have a problem with a particular credit card vendor.

Guarantee and credit limit are positively correlated (0.204) whereas credit limit varies from branch to branch (-0.127). Frequency of withdrawals also depends on the branch in which the credit card holder is from, the correlation is (-0.107). Excess above limit is negatively correlated to marital status.

The correlation between excess above limit (EAL) and number of payment in arrears is one of the highest (0.479) bounce payments and EAL is 0.512; and bounced payment and number of payments in arrears is 0.537. Again, the number of payments in arrears varies from branch to branch (-0.114). As expected, the number of payment is arrears (NOPIAAR) is positively correlated to loan arrears (0.887). Guarantee is negatively correlated to bounced payments i.e. default rate is less in case of guaranteed loans. In general, most of the predictor variables are not highly correlated.

4.6 Box M Test

Table 7a : Box's Test of Equality of Covariance Matrices

Log Determinants		
Class	Rank	
[illegible]	14	4.907
[illegible]	13	.a
Pooled within-groups	14	1.989

Pooled with the ranks and natural logarithms of determinants printed are those of the group covariance matrices in-groups a = Singular.

Box M Tests is about testing the assumption of equality of covariance across groups. The results are summarized in Table 7. Larger log determinants correspond to more variable groups. Large differences in log determinants indicate groups that have different covariance matrices. In this case, no test can be performed with fewer than two non-singular group covariance matrices.

4.7 Standardized Canonical Discriminant Function

Table 8 : Standardized Canonical Discriminant Function Coefficients

	Function		Scores After Ranking	
	1			
MARITAL	-0.0782		LOARREAC	0.9813
AGE	0.0400		FOLP	0.4229
EMPCLCD	-0.0565		EAL	0.3643
NOCRH	0.2077		NOCRH	0.2077
NOLOAN	0.1458		NOLOAN	0.1458
MPR	0.0423		MPR	0.0423
CRLIMCL	-0.1331		AGE	0.0400
FOCW	-0.4034		BOUPAY	0.0360
FOLP	0.4229		BRANCHC	-0.0193
EAL	0.3643		EMPCLCD	-0.0565
NOPIARR	-0.3048		MARITAL	-0.0782
BOUPAY	0.0360		CRLIMCL	-0.1331
BRANCHC	-0.0193		NOPIARR	-0.3048
LOARREAC	0.9813		FOCW	-0.4034

The standardized coefficients in Table 8 allow you to compare variables measured in different scales. Coefficients with large absolute value correspond to variables with greater discriminating ability. The results are that the variables with the highest coefficients are loan arrears ((0.9813), excess above limit (0.3643) number of credit cards held (0.4229) and no of loans (0.1458). These are almost same variables chosen when test of equality of mean approaches was adopted.

4.8 Structure Matrix

This matrix highlights (Table 9) the correlation of each predictor variable with the discriminant function.

Table 9 : Structure Matrix

	Function			
	Not Ranked		Scores After Ranking	
	1			
LOARREAC	0.7813		LOARREAC	0.7813
BOUPAY	0.5250		BOUPAY	0.5250
NOPIARR	0.4780		NOPIARR	0.4780
FOLP	0.4494		FOLP	0.4494
EAL	0.4491		EAL	0.4491
NOCRH	0.1960		NOCRH	0.1960
FOCW	0.1521		FOCW	0.1521
NOLOAN	0.1032		NOLOAN	0.1032
MPR	0.0996		MPR	0.0996
MARITAL	-0.0980		EMPCLCD	0.0690
EMPCLCD	0.0690		CRLIMCL	-0.0368
AGE	-0.0394		BRANCHC	-0.0392
BRANCHC	-0.0392		AGE	-0.0394
CRLIMCL	-0.0368		MARITAL	-0.0980

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.

The ordering in Table 9 is almost same as suggested by test of equality of group means and is different from that of standardized coefficients (see Table 8).

In table 8, frequency of late payment is ranked 4, and it is replaced by bounced payments (BOUPAY). This disagreement could be due to the collinearity between the two variables as noted in the correlation matrix table (see appendix 7). The same applies to the positions. Multicollinearity has the effect of inflating the impact of a predictor variable.

4.9 Summary Of Canonical Discriminant Functions

There are two of them – Eignevalues and Wilk's lambda are presented in form of a table – Table 10.

Table 10 : Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation	
1	14.934	100	100	0.968	

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	0.063	526	14	0.00

The eignevalues (first part of table 10) provides information about the relative efficiency of each discriminant function. When there are two groups such as bad and good credit card holders, the canonical correlation is the most useful measure and it is considered to be equivalent to Pearson's correlation between the discriminating scores and the groups.

Wilk's lambda is a measure of how well each function separates the cases into groups e.g. which group does case B0. 20 or 30 belong to? Wilk's lambda indicates the proportion of total variance in the discriminant scores not explains by differences among the groups. Therefore, smaller values of Wilk's lambda indicate greater discriminating ability of the function. In Table 10, the Wilk's lambda score is 0.063 confirming greater discriminating power of the discriminating variables.

The chi square on the table tests the hypothesis that the means of the function listed are equal across groups. The small significance value of 0.00 indicates that the discriminant function in Table 11 does better than chance at separating bad credit card holders from good credit card holders.

Table 11 : Final Discriminating Function

Variable	Coefficient
MARITAL	-0.219
AGE	0.007
MPCLCD	-0.026
NOCRH	0.235
IOLOAN	0.161
PR	0.148
CRLIMCL	-0.109
OCW	-0.148
OLP	0.249
EAL	2.406
OFIARR	-0.232
OUPAY	0.035
RANCHC	-0.002
LOARREAC	0.816
(Constant)	-4.655

Coefficients of variables of high values and positive signs such as excess above limit [EAL (2.406)], loans in arrears [LOARREAC (0.816)], and number of credit cards held [NOCRH (0.235)], indicate important predictive powers of these factors in the determination of good from risky applicants.

The practical result of using the discriminant model (discriminant function) and coefficients on Table 11 are summarized in Table 12 and Appendix 8. The discriminant scores or z-scores for each case are summarized on Function 1.

4.9.1 Case Wise Statistics

Bayes Theorem provides a means to transform prior probabilities into posterior probabilities. In the case of our discriminant function analysis, prior probabilities P(G) are transformed into the posterior probabilities of group membership given a particular score P(G/D) using information about the discriminating variables. Interpretation of P(D/G) is the likelihood of membership in a group given a particular score. In some cases involving extreme scores, the likelihood of belonging to either group will be small. In other cases involving scores that fall almost equidistant from either mean, the likelihood of belonging to either group will be similar. Rather than simply observing predicted group membership, probabilities of membership in all groups is presented see appendix 8.

Table 12: Classification Results

			Predicted Group Membership		Total
		CLASS	0	1	
Original	Count	0	100	0	100
		1	0	99	99
	%	0	100	0	100
		1	0	100	100
Cross-validated	Count	0	100	0	100
		1	0	99	99
	%	0	100	0	100
		1	0	100	100

A cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the function c 100.0% of cross-validated grouped cases correctly classified.

Key : 0 = Credit Card Holders Classified as Bad
1 = Credit Card Holders Classified as Good.

The classification table, as presented in table 12, summarizes the classification results and show that 100 percent (%) of the cases are classified correctly. This suggests that in overall, the model specified in Table 11 is correct.

These findings qualify multiple discriminant analysis, credit scoring technique as applicable for assessment of good credit risks from bad credit risks on potential card applicants, using observable objective personal traits to compare a potential borrower with past borrowers. These results are consistent with those of Schreiner (1999), but as he cautions, human input by loan officers cannot completely be eliminated. This is true where some variables [with reference to this study] such as town, nationality and guarantee were found to have little discriminant power as opposed to majority of factors considered in the analysis like marital status.

The outcome of this analysis also supports findings by Thomas (2000), that perfect classification is impossible for reasons such as 'good' applicants having the same characteristics as 'bad' applicants. This was evident in his study where majority of cardholders [good and bad] were Kenyans with an average age of 36 – 37 years.

CHAPTER FIVE

5.0 SUMMARY OF FINDINGS, CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

5.1 Summary Of Findings

The study was conducted with the aim of establishing whether the Multiple Discriminant Analysis Technique (MDA) can be useful to actual lending situation. A discriminant function was estimated from the pool of credit cards that had already been granted. A classification rule was then formulated, designed to distinguish, or discriminate between the groups of good and bad cardholders, while minimizing the overall error rates or costs of misclassification.

Various characteristics of an individual were quantitatively rated to arrive at a credit decision. Point values were assigned to various credit qualities or characteristics found on a credit application.

On the basis of an average weighted overall score provided by this technique, an applicant is judged to be a good or bad credit risk.

From the findings of the study, it has emerged that MDA can be used to accurately predict credit card failure. These findings provide an insight into the characteristics and practices of successful credit card lending financial institutions in terms of profitability and agree with Asch (1995) and Thomas (2000). This is a very important issue for bank management, policy makers and shareholders.

Specifically, this study found out that default rate is less in cases of guaranteed credit card. The higher the number of loans a cardholder had with the bank and other financial institutions, the more the number of credit card payments in arrears (number of payment is arrears (NOPIAAR) is positively correlated to loan arrears (0.887)). As expected, this is as a result of customer financial over commitment.

Cardholders with repayment constraints tend to hold more than one credit card.

Variables such as age, branch and annual income are not important discriminating factors between good and bad cardholders while number of loans in arrears, excess above limit and number of credit cards held are significant in credit risk determination. While age did not come out as a strong discriminant variable, this could be attributable to the fact that the average age for both good and bad credit card holders was around 36 years. It is however, expected that default rate is higher for customers ranging between 20-30years due to extravagant and unbudgeted spending.

Guarantee was not a significant variable in credit risk determination because only customers applying for a credit limit of K.shs. 20,000 and above are required to secure the borrowing by means of guarantees. However being a mass-market consumer credit sector, majority of customers borrow between K.shs. 20.000 – 100,00, thus not required to produce a guarantee cover.

The branch and annual salary emerged as poor discriminant factors. This is because irrespective of the branch a client belongs to, when annual income is considered in isolation with other factors such as monthly salary borrowing commitments, it could qualify extension of credit to non qualified [bad] applicants, due to net income over commitments.

The above findings provide an insight into the characteristics and practices of successful lenders in the credit card industry in terms of profitability.

The findings also suggest that there is a real need for government intervention in this sector to improve access to high quality credit while reducing the uncertainties facing players in the credit card sector when making lending decisions. This is important for stability within the sector and the economy as a whole.

Although MDA seeks to minimize or completely eliminate the judgment of the credit decision maker from the credit process, total scores that almost made credit be accepted may be looked at more carefully with an aim of applying a judgment process to extend credit.

5.2 Conclusions

In view of these findings, the following conclusions can be made which may be useful to the management, policy makers and shareholders.

This paper has shown that MDA technique can be applied successfully in estimating credit card default risk by distinguishing card holders as either "good" in which case they are either current or they have been paid off, or as "bad" in which case they are slow paying delinquent or in default.

It is equally true that some variables in use by some credit managers lack discriminating power. These are age, branch, annual income and guarantee. In the determination of which applications should be given a credit card and which ones should not, credit managers should disregard these variables and accord more weight to stronger discriminant variables such as number of loans with financial institutions, number of credit cards held and marital status. Any divergence from this conclusion could result to inconsistency to the organizations credit policy, where non-qualified applicants get approval for credit while qualified ones are denied.

These findings are an important step in making the scrutinizing of credit card loans more feasible therefore allowing better diversification of risk.

Some banks are able to extend more safe loans under credit scoring than under judgmental credit approval systems (Asch,1995). Credit scoring encourages more lending because it gives banks a tool for more accurately pricing risk. This is attributable to improved objectivity in the loan approval process that ensure they apply same underwriting criteria to all borrowers regardless of race, gender or other factors prohibited by law from being used in credit decisions.

The accuracy of a credit scoring system depends on the care with which it is developed. Even if the lender can lower its costs of evaluating credit card applications by using a scoring technique such as MDA, these cost savings would be eroded by poor performing credit card loans. A good scoring model should therefore be built around sufficient historical data, which reflects loan performance in periods of both good and bad economic conditions.

5.3 Limitations Of the Study

The degree to which the findings of this study may be generalized should be ascertained in the light of the following limitations.

i. Due to the strict confidentiality of banking information, data was not obtainable from all credit card lending institutions.

ii. Actual size of portfolios was also not available while risk assessment/credit scoring criteria used by other institutions could not be established.

5.4 Suggestions For Further Research

This study may be viewed as a starting point for several other related studies within the lending environment because so far no other research has been done in Kenya directly related to it.

i. This study focused only on Barclaycard to draw conclusions for the entire credit card sector. A further research may extend this analysis to include all other credit card issuers such as KCB and Cooperative Bank, to establish whether results would be significantly different.

ii. An investigation could also be undertaken to evaluate the suitability of Multiple Discriminant Analysis in credit risk assessment for personal bank loans, overdrafts and mortgages.

iii. While the findings of this investigation are expected to be significant only in the credit card industry, a similar study could be carried out in all financial institutions engaged in all categories of lending, with an aim of coming up with a standard credit scoring model that can be relied upon within the Kenyan environment.

iv. Research could also be conducted to investigate the weaknesses in the regulatory framework of the financial system that needs to be addressed in order to enhance efficient credit card risk assessment on credit card borrowers. This is because the failure/bankruptcy of one credit card financial institution due to default, could lead to the failure of other financial institutions thus destabilizing the entire economy.

v. A related enquiry may be conducted using a different model of analysis other than MDA such as regression and factor analysis to establish whether it could yield results of better significance.

Appendix 1 Data For Final Analysis

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
1	1	0	1	1	35	BASFEA LTD	Private	1	0	1	1293700	3	1	3	2	0.25	150000	4	8	3	0.35	3	5	0	DIANI	1	1	90	7
3	3	0	0	1	31	TSC	Gov	2	1	1	490000	1	0	3	1	0.1	150000	4	3	3	0.5	5	3	0	QUEENSWAY	3	1	150	9
4	4	0	0	1	30	ZANCO AGENCIES	Private	1	0	1	960000	3	0	3	2	0.1	25000	1	2	3	0.5	5	3	0	KERICHO	4	0	150	9
5	5	0	1	1	38	DIAMOND MEDICAL SVCS	Private	1	1	1	1000000	3	0	2	0	0.1	150000	4	2	5	0.5	5	3	0	QUEENSWAY	5	1	150	9
6	6	0	1	1	42	SELF EMPLOYED	Self	3	1	1	790000	3	0	1	1	0.6	50000	1	2	3	0.5	5	6	0	QUEENSWAY	5	0	150	9
7	7	0	1	1	32	KENYA PIPELINE CO. LTD	Para	4	1	1	635448	2	0	1	0	0.2	50000	1	5	3	0.42	5	3	0	QUEENSWAY	5	0	150	9
8	8	0	1	1	32	EAST AFRICAN CONFERENCE	Private	1	1	1	3078000	4	1	1	3	0.2	300000	4	5	4	0.55	3	2	1	WESTLANDS	6	0	90	7
9	9	0	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	760000	3	0	1	3	0.2	100000	4	5	8	0.3	3	4	0	QUEENSWAY	5	0	90	7
10	10	0	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	1250000	3	0	4	3	0.2	140000	4	12	8	1.1	3	4	0	MUTHAIGA	7	0	90	7
11	11	0	1	1	38	KTDA	Para	4	0	1	1678812	4	1	1	3	0.5	130000	4	6	8	0.42	4	4	0	WESTLANDS	6	0	120	8
12	12	0	1	1	46	INFINITY ADVERTISING	Private	1	1	1	300000	1	1	2	2	1	65000	2	5	6	0.48	4	4	0	HAILE SELLASIE	8	0	120	8
13	13	0	1	1	42	INDONESIAN EMBASSY	Inter	6	1	0	3480000	4	1	2	1	0.8	70000	2	5	3	0.48	4	4	0	MARKET	9	0	120	8
14	14	0	0	1	28	THEMIS INVESTMENTS LTD.	Private	1	1	1	1968000	4	1	2	1	0.3	100000	4	2	3	0.51	4	4	0	MARKET	9	1	120	8
15	15	0	0	1	30	SATEL ENGINEERS	Private	1	1	1	1200000	3	1	1	1	0.3	80000	3	1	3	0.34	8	4	0	QUEENSWAY	5	1	240	11
16	16	0	1	1	35	RETIRED	Retired	7	0	1	475000	1	1	1	5	0.6	128000	4	7	3	0.41	8	4	0	NKRUMAH RD	10	1	240	11
17	17	0	1	1	33	TELCOM	Para	4	1	1	750000	3	1	1	2	0.1	50000	1	3	3	0.33	9	3	0	KAREN	11	1	270	11
18	18	0	0	1	32	KTDA	Para	4	1	1	1104000	3	0	1	1	0.1	50000	1	3	3	0.4	8	2	0	HURLINHAM	7	1	240	11
19	19	0	1	1	32	MARSHALLS E.A. LTD	Private	1	0	1	600000	2	1	3	1	0.1	50000	1	3	7	0.65	8	5	0	KAKAMEGA	12	0	24	5
20	20	0	0	1	32	TELCOM	Para	4	0	1	316000	1	1	1	1	0.1	50000	1	3	9	0.3	8	6	0	NKRUMAH RD	10	0	240	11
21	21	0	1	1	39	KENYA ARMED FORCES	Forces	5	1	1	360000	1	0	4	1	1	100000	4	2	9	0.3	5	6	0	QUEENSWAY	5	0	150	9
22	22	0	1	1	43	KENYA PIPELINE CO. LTD	Para	4	1	1	780000	3	0	4	0	1	70000	2	8	9	0.44	5	6	0	QUEENSWAY	5	1	150	9
23	23	0	0	1	32	KENYA UTALII COLLEGE	Para	4	1	1	500000	1	0	3	3	0.2	50000	1	10	12	0.8	5	6	0	QUEENSWAY	5	0	150	9
24	24	0	1	1	35	TELCOM	Para	4	1	1	500000	1	0	1	3	1	80000	3	4	5	0.75	6	5	0	ENTERPRISE ROAD	13	0	180	10
25	25	0	1	1	40	TELCOM	Para	4	1	1	1904000	4	0	2	3	1	66000	2	3	5	0.6	3	4	0	QUEENSWAY	5	0	90	7
2	26	0	1	1	42	AERO SUPPORT LTD	Private	1	0	1	600000	2	0	3	4	0.1	70000	2	12	3	0.67	8	3	0	ELDORET	2	1	90	7

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
26	26	0	1	1	46	SELF	Para	4	1	1	3150000	4	1	2	2	0.1	80000	3	3	6	0.46	6	3	0	WESTLANDS	6	0	180	10
27	27	0	1	1	36	KENYA ARMED FORCES	Forces	5	1	1	360000	1	1	2	1	0.1	80000	3	9	6	0.5	4	3	0	QUEENSWAY	5	1	120	8
28	28	0	1	1	36	KENYA PIPELINE CO. LTD	Forces	5	1	1	696000	2	1	3	1	0.1	50000	1	11	6	0.5	4	3	0	QUEENSWAY	5	0	120	8
29	29	0	1	1	41	SELF EMPLOYED	Self	3	1	1	2155200	4	0	2	1	0.8	100000	4	5	6	0.39	4	4	0	QUEENSWAY	5	0	120	8
30	30	0	1	1	39	SELF	Self	3	0	1	480000	1	0	2	1	0.8	25000	1	2	6	0.28	3	4	0	KISII	14	0	90	7
31	31	0	1	1	36	SELF	Self	3	1	1	389000	1	0	2	1	0.8	50000	1	2	6	0.3	3	4	0	MARKET	9	0	90	7
32	32	0	0	0	29	D.T.DOBIE	Private	1	1	1	528000	1	0	2	1	0.8	50000	1	2	12	0.3	3	3	0	PLAZA	15	0	90	7
33	33	0	0	1	33	AVENTIS CROPSCIENCE	Private	1	1	1	720000	2	0	3	1	0.6	50000	1	3	3	0.56	7	6	0	ENTERPRISE ROAD	13	0	210	10
34	34	0	1	1	39	DOD KENYA NAVY	Forces	5	0	1	772440	3	0	3	2	0.2	40000	1	6	8	0.77	6	6	0	NAKURU EAST	15	1	180	10
35	35	0	1	1	58	RETIRED	Retired	7	1	1	1470312	3	0	1	2	0.5	100000	4	7	8	0.36	6	5	0	QUEENSWAY	5	0	180	10
36	36	0	1	0	36	KASWA LTD	Private	1	1	1	720000	2	0	2	2	0.5	70000	2	7	8	0.49	6	5	0	QUEENSWAY	5	0	180	10
37	37	0	0	0	30	KENYA AIRWAYS	Private	1	1	1	1140000	3	0	2	2	0.5	50000	1	15	8	1.05	8	5	0	QUEENSWAY	5	0	240	11
38	38	0	1	1	35	KENYA POWER & LIGHTING	Private	1	1	1	1313968	3	0	2	2	0.5	70000	2	8	8	0.4	5	5	0	QUEENSWAY	5	1	150	9
39	39	0	1	1	35	KENYA BREWERIS LTD	Private	1	1	1	1657704	4	0	2	2	0.8	90000	3	5	8	0.4	5	5	0	QUEENSWAY	5	1	150	9
40	40	0	1	1	34	KENYA ARMED FORCES	Forces	5	1	1	862000	3	0	2	2	0.6	50000	1	5	10	0.45	7	5	0	QUEENSWAY	5	0	210	10
41	41	0	1	0	31	EAST END PLAZA NAIROBI WEST	Private	1	1	1	4680000	4	0	2	2	0.3	50000	1	5	4	0.75	5	3	0	QUEENSWAY	5	0	150	9
42	42	0	0	1	29	COMMERCIAL BANK OF AFRICA	Bank	8	0	1	887232	3	1	2	2	0.3	60000	2	5	7	0.6	3	3	0	WESTLANDS	6	0	90	7
43	43	0	1	1	42	EABS	Private	1	1	1	1081368	3	1	1	2	0.6	50000	1	9	12	0.9	8	5	0	WESTLANDS	6	0	240	11
44	44	0	1	1	40	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1424000	3	1	1	3	0.5	76000	3	13	5	0.95	9	5	0	WESTLANDS	6	0	270	11
45	45	0	1	1	38	K T D A	Para	4	0	1	1216020	3	1	1	2	0.4	50000	1	2	5	0.43	3	3	0	MERU	16	0	90	7
46	46	0	1	1	38	SELF-INTRA DELTA CO LTD	Private	1	1	1	1200000	3	0	2	3	0.1	30000	1	2	5	0.3	3	3	0	WESTLANDS	6	0	90	7
47	47	0	1	1	34	SELF	Self	3	1	1	3600000	4	0	3	3	0.1	90000	3	1	5	0.4	4	3	0	WESTLANDS	6	0	120	8
48	48	0	1	1	32	IMPALA GLASS IND LTD	Private	1	1	1	480000	1	1	2	3	0.2	80000	3	1	8	0.4	3	3	0	QUEENSWAY	5	0	90	7
49	49	0	1	1	45	SOTIK TEA COMPANY LTD	Private	1	0	1	1866000	4	1	1	2	0.2	40000	1	1	3	0.4	3	3	0	THIKA	17	0	90	7
50	50	0	1	1	43	ASK	Para	4	1	1	700000	2	1	4	2	0.2	160000	4	2	7	0.36	3	3	0	ENTERPRISE ROAD	13	0	90	7
51	51	0	1	0	38	ISRAEL AIRLINES LTD	Private	1	1	1	956000	3	1	1	2	0.2	50000	1	1	7	0.2	5	3	0	KAREN	11	1	150	9
52	52	0	1	1	46	SELF-MWEA MEDICAL CENTRE	Private	1	0	1	2000000	4	1	1	1	0.2	66000	2	1	7	0.25	2	4	0	EMBU	18	1	60	6

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
53	53	0	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	480000	1	1	2	4	1	30000	1	8	4	0.74	3	4	0	RUARAKA	19	1	90	7
54	54	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	731000	2	1	2	4	0.2	60000	2	12	7	0.92	3	3	0	NIC HSE	20	1	90	7
55	55	0	1	1	48	KENYA PIPELINE CO. LTD	Para	4	0	1	960000	3	1	2	1	1	50000	1	7	7	0.7	3	3	0	BUNGOMA	21	0	90	7
56	56	0	0	1	35	NYAGA NYAMU AND CO	Private	1	0	1	800000	3	0	1	0	1	66000	2	7	9	0.68	6	5	0	MERU	22	0	180	10
57	57	0	1	1	43	DOD	Forces	5	1	1	695188	2	0	3	0	0.6	30000	1	7	3	0.4	6	5	0	QUEENSWAY	5	1	180	10
58	58	0	0	1	35	DOD	Forces	5	1	1	1225160	3	0	2	0	0.6	70000	2	8	8	0.6	6	5	0	NIC HSE	20	0	180	10
59	59	0	1	1	38	UNIVERSITY OF NAIROBI	Para	4	1	1	750000	3	0	1	1	0.1	40000	1	6	8	0.6	4	5	0	QUEENSWAY	5	1	120	8
60	60	0	0	1	32	S D CONSTRUCTION LTD	Private	1	1	1	960000	3	0	1	4	0.1	100000	4	3	8	0.35	4	5	0	QUEENSWAY	5	1	120	8
61	61	0	1	1	38	DOD	Forces	5	1	1	2760000	4	1	3	6	0.1	100000	4	16	8	1.25	10	9	0	QUEENSWAY	5	0	300	11
62	62	0	0	1	34	KENYA BREWERIES LTD	Private	1	0	1	1611444	4	0	3	1	1	100000	4	2	9	0.2	3	2	0	WESTLANDS	6	0	90	7
63	63	0	1	1	34	AMOS AUTO GARAGE	Private	1	1	1	600000	2	0	1	0	0.75	100000	4	6	6	0.4	6	3	0	WESTLANDS	6	0	180	10
64	64	0	1	1	38	DOD	Forces	5	1	1	810000	3	1	1	1	0.6	70000	2	4	6	0.4	6	4	0	MOI AVENUE	23	0	180	10
65	65	0	1	1	36	SULMAC CO LTD	Private	1	1	1	1188000	3	0	2	2	0.5	100000	4	3	6	0.28	3	3	0	MOI AVENUE	23	1	90	7
66	66	0	1	1	41	DOD	Forces	5	1	1	720000	2	0	2	2	0.6	40000	1	3	6	0.25	3	3	0	MOI AVENUE	23	1	90	7
67	67	0	0	1	30	BEATMAN AND BATON LTD	Private	1	1	1	1360000	3	0	2	2	0.5	70000	2	3	4	0.3	3	3	0	MUTHAIGA	7	1	90	7
68	68	0	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	1373060	3	0	1	2	0.5	60000	2	3	11	0.3	3	3	0	MUTHAIGA	7	1	90	7
69	69	0	1	1	42	SELF EMPLOYED	Self	3	1	1	898000	3	0	1	2	0.5	130000	4	8	8	0.62	4	4	0	MOI AVENUE	23	1	120	8
70	70	0	1	1	34	N S S F	Para	4	1	1	1043160	3	0	1	2	0.5	40000	1	11	8	0.93	7	6	0	WESTLANDS	6	1	210	10
71	71	0	0	0	32	TSC	Gov	2	1	1	780000	3	0	1	3	0.75	50000	1	7	3	0.44	3	3	0	MOI AVENUE	23	0	90	7
72	72	0	1	1	35	KENYA BOOM TRADERS	Private	1	1	1	690000	2	0	3	3	0.25	128000	4	6	4	0.45	5	3	0	MOI AVENUE	23	1	150	9
73	73	0	0	1	29	TRANSNATIONAL BANK	Bank	8	1	1	1414200	3	1	3	2	0.25	40000	1	3	4	0.3	3	3	0	QUEENSWAY	5	1	90	7
74	74	0	0	1	33	TRANSAMI KENYA LTD	Private	1	1	1	1128000	3	0	3	4	0.2	66000	2	6	3	0.75	6	5	0	MOI AVENUE	23	0	180	10
75	75	0	1	1	43	KENYA ANTI CORRUPTION COMMISSION	Para	4	0	1	620000	2	0	3	1	0.25	128000	4	6	9	0.75	6	5	0	KISII	14	0	180	10
76	76	0	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1200000	3	1	4	1	0.75	120000	4	6	6	0.65	5	5	0	QUEENSWAY	5	0	150	9
77	77	0	1	1	37	KENYA POWER & LIGHTING	Para	4	1	1	1200000	3	1	1	1	0.3	100000	4	2	6	0.3	3	4	0	MOI AVENUE	23	0	90	7
78	78	0	1	1	48	KUTUS AUTO H/WARE LTD	Private	1	0	1	480000	1	1	2	0	0.3	50000	1	2	6	0.31	3	3	0	KERUGOYA	24	0	90	7
79	79	0	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	614960	2	1	2	3	0.4	100000	4	5	6	0.5	4	3	0	MOI AVENUE	23	0	120	8

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
80	80	0	1	1	42	KENYA AIRPORTS AUTHORITY	Para	4	0	1	1200000	3	0	1	3	0.1	50000	1	5	6	0.45	3	3	0	BUNGOMA	21	0	90	7
81	81	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	468000	1	1	3	3	0.1	80000	3	10	4	0.86	8	6	0	MOI AVENUE	23	0	240	11
82	82	0	1	1	36	CENTRAL BANK OF KENYA	Bank	8	1	1	3110205	4	0	1	2	0.1	240000	4	6	6	0.6	4	3	1	MOI AVENUE	23	0	120	8
83	83	0	1	1	28	COCA COLA NORTHERN AFRICA	Private	1	1	1	960000	3	0	1	2	0.8	96000	4	5	6	0.6	4	3	0	WESTLANDS	6	0	120	8
84	84	0	0	1	31	B A T (K) LTD	Private	1	1	1	960000	3	0	1	1	0.6	50000	1	5	6	0.62	5	4	0	MOI AVENUE	23	1	150	9
85	85	0	0	0	28	ROYAL INSURANCE OF E.A.	Private	1	1	1	1800000	4	0	1	1	0.6	100000	4	5	3	0.47	4	4	0	QUEENSWAY	5	0	120	8
86	86	0	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	219600	1	0	1	2	0.5	60000	2	6	3	0.7	6	4	0	QUEENSWAY	5	0	180	10
87	87	0	0	1	30	DEL-MONTE (K) LTD	Private	1	1	1	2028480	4	0	1	2	0.5	50000	1	4	3	0.4	3	4	0	QUEENSWAY	5	0	90	7
88	88	0	1	1	42	KENYA PORTS AUTHORITY	Para	4	0	1	1521720	4	0	2	2	0.8	86000	3	1	7	0.35	2	3	0	NKRUMAH RD	10	0	60	6
89	89	0	1	1	37	KENYA AIRPORTS AUTHORITY	Para	4	0	1	485000	1	0	2	2	0.8	50000	1	8	4	0.75	6	6	0	NKRUMAH RD	10	1	180	10
90	90	0	0	1	33	TSC	Gov	2	1	1	665000	2	0	2	2	1	182000	4	12	8	0.8	6	5	0	MARKET	9	1	180	10
91	91	0	1	1	35	TSC	Gov	2	1	1	1255200	3	0	3	2	1	75000	3	4	3	0.5	5	5	0	MOI AVENUE	23	1	150	9
92	92	0	0	1	28	SAVAGE PARADISE LTD	Private	1	1	1	540000	1	0	1	2	0.75	50000	1	5	5	0.55	3	4	0	QUEENSWAY	5	1	90	7
93	93	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	1176000	3	0	1	2	0.6	50000	1	5	5	0.4	4	4	0	MOI AVENUE	23	1	120	8
94	94	0	0	1	34	TRADE WINGS INTERNATIONAL LTD	Private	1	1	1	1500000	4	0	4	2	0.75	76000	3	14	5	0.9	9	10	0	HAILE SELLASIE	8	0	270	11
95	95	0	1	0	35	STANDARD BANK(EX-STAFF)	Bank	8	1	1	1920000	4	1	1	2	0.8	100000	4	6	11	0.75	6	8	0	HAILE SELLASIE	8	0	180	10
96	96	0	1	1	42	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	296000	1	0	1	1	1	200000	4	3	6	0.39	4	5	0	RUARAKA	19	0	120	8
97	97	0	1	1	56	POSHO MILL	Private	1	0	1	226000	1	0	1	3	1	66000	2	3	6	0.6	4	5	0	NYAHURURU	25	0	120	8
98	98	0	1	1	38	KENYA POWER & LIGHTING	Para	4	1	1	315000	1	0	2	3	0.1	60000	2	2	6	0.55	4	4	0	MOI AVENUE	23	0	120	8
99	99	0	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	600000	2	1	2	4	0.1	70000	2	9	3	0.37	3	4	0	QUEENSWAY	5	0	90	7
100	100	0	0	1	29	STANDARD CHARTERED	Bank	8	1	1	2068560	4	0	2	1	0.8	80000	3	11	8	0.88	7	8	0	WESTLANDS	6	0	210	10
1	101	1	1	1	46	ABBEY INVESTMENTS LTD	Private	1	1	1	623000	2	0	1	1	0.2	195000	4	2	0	0	0	0	0	WESTLANDS	6	0	0	1
2	102	1	1	1	52	SHAH MUNGE & PARTNERS LTD	Private	1	1	1	480000	1	1	0	1	0.5	150000	4	1	0	0	0	0	0	QUEENSWAY	5	0	0	1
3	103	1	1	1	42	EAST AFRICAN CEMENT	Private	1	1	1	615000	2	0	0	1	0.1	96000	4	3	0	0	0	0	0	QUEENSWAY	5	1	0	1
4	104	1	1	1	59	NAIROBI CITY COUNCIL	Para	4	1	1	380000	1	1	0	1	0.1	66000	2	3	1	0.02	0	0	0	QUEENSWAY	5	0	0	1
5	105	1	1	1	54	GENERAL ACCIDENT INSURANCE CO.	Private	1	1	1	750000	3	1	2	1	0.2	100000	4	5	0	0	0	0	0	QUEENSWAY	5	1	2	3
6	106	1	1	1	47	MITSUBISHI CORPORATION	Private	1	1	1	727200	2	1	1	1	0.3	150000	4	0	0	0	0	0	0	QUEENSWAY	5	1	0	1

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
7	107	1	1	1	49	FIRESTONE (E.A) 1969 LTD	Private	1	0	1	480000	1	0	2	1	0.5	66000	2	0	0	0	0	0	0	NKRUMAH ROAD	10	0	0	1
8	108	1	1	1	35	FIRESTONE E.A.(1969)LTD	Private	1	1	1	400000	1	0	2	1	0.1	50000	1	1	0	0	0	0	0	HURLINGHAM	7	0	0	1
9	109	1	1	1	45	GREENSTATES SCHOOL	Private	1	0	1	840000	3	1	1	2	0.1	66000	2	2	0	0	0	0	0	THIKA	17	1	8	3
10	110	1	1	1	42	KENYA POWER & LIGHTING CO.LTD	Para	4	1	1	648000	2	1	0	1	0.1	91000	3	2	0	0	0	0	0	WESTLANDS	6	1	1	2
11	111	1	1	1	48	COOPERS & LYBRAND	Private	1	1	1	996000	3	1	0	1	1	50000	1	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
12	112	1	1	1	36	VICTORIA COMMERCIAL BANK	Bank	8	1	1	700200	2	1	0	1	0.8	100000	4	2	0	0	0	0	0	MARKET	9	1	0	1
13	113	1	1	1	42	CONSTRUCTION PROJECT CONSULTAN	Private	1	0	1	727560	2	0	0	1	0.3	50000	1	6	0	0	0	0	0	KITALE	26	1	0	1
14	114	1	1	1	45	KENYA POWER & LIGHTING CO.LTD	Private	1	1	1	840000	3	1	0	1	0.1	200000	4	3	0	0	0	0	1	ENTERPRISE RD	13	1	0	1
15	115	1	1	0	39	GLAXO WELLCOME (K) LTD	Private	1	1	1	600000	2	0	2	1	0.1	50000	1	3	0	0	0	0	0	WESTLANDS	6	1	0	1
16	116	1	0	1	33	MICRO REGISTRARS LTD	Private	1	1	1	1124000	3	1	0	1	0.1	75000	3	2	0	0	0	0	0	MARKET	9	1	0	1
17	117	1	1	0	40	SELF EMPLOYED (GR COLLECTIONS)	Self	3	1	1	690192	2	1	3	1	0.2	200000	4	2	0	0	0	0	1	QUEENSWAY	5	0	0	1
18	118	1	1	1	31	CUSSONS	Private	1	1	1	720000	2	0	1	1	0.1	100000	4	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
19	119	1	0	0	28	AIRLINK LTD	Private	1	1	1	372000	1	1	0	1	0.1	76000	3	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
20	120	1	1	1	44	MIGITI ENTERPRISES LTD	Private	1	1	1	720000	2	1	0	1	0.1	92000	3	1	0	0	0	0	0	KAREN	11	1	0	1
21	121	1	1	0	32	I.C.A.O	Private	1	1	1	456000	1	1	0	2	0.5	128000	4	1	1	0.1	0	1	0	WESTLANDS	6	1	12	4
22	122	1	1	1	29	YAKO LTD	Private	1	0	1	96000	1	1	0	2	0.1	50000	1	1	0	0	0	0	0	NAKURU EAST	15	1	0	1
23	123	1	1	1	36	BAT (K) LTD	Private	1	1	1	589000	2	1	0	1	1.1	40000	1	0	0	0	0	0	0	HURLINGHAM	7	1	0	1
24	124	1	1	1	33	DEL MONTE KENYA LTD	Private	1	0	0	1046964	3	0	0	1	0.5	150000	4	5	0	0	0	0	0	THIKA	17	1	0	1
25	125	1	1	1	42	BHOGAL'S GARAGE LTD	Private	1	0	1	3000000	4	1	0	1	0.1	66000	2	1	0	0	0	0	0	MOI AVENUE	23	1	0	1
26	126	1	1	1	38	PFIZER LABS	Private	1	1	1	900000	3	1	0	1	0.1	50000	1	1	0	0	0	0	0	MOI AVENUE	23	0	1	2
27	127	1	1	1	38	CARNAUDMETAL BOX K LTD	Private	1	1	1	1399200	3	1	0	1	0.1	96000	4	2	0	0	0	0	0	MOI AVENUE	23	0	0	1
28	128	1	1	1	32	M PINNACLE ENG/HARD WARE	Private	1	1	1	1400000	3	1	1	1	0.2	60000	2	4	0	0	0	0	0	MOI AVENUE	23	0	0	1
29	129	1	1	1	41	FINERALF FOREX BUREAU	Private	1	1	1	1200000	3	0	0	1	0.1	150000	4	6	0	0	0	0	0	MOI AVENUE	23	0	0	1
30	130	1	1	1	46	BARKER & BARTON (K) LTD	Private	1	1	1	1000000	3	1	2	1	0.3	86000	3	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
31	131	1	1	1	37	DYER AND BLAIR LTD	Private	1	1	1	1020000	3	1	2	1	0.1	81000	3	2	0	0	0	0	0	MARKET	9	0	0	1
32	132	1	1	1	39	LIVINGSTONE REGISTRARS LTD	Private	1	1	1	1260000	3	1	1	1	0.1	66000	2	2	0	0	0	0	0	MARKET	9	0	0	1
33	133	1	1	1	41	AKIBA BANK LTD	Bank	8	1	1	1140000	3	1	0	1	0.1	86000	3	2	0	0	0	1	0	MARKET	9	0	5	3

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
34	134	1	0	1	30	ABERCROMBIE & KENT [COAST] LTD	Private	1	0	1	330000	1	1	0	1	0.1	70000	2	2	0	0	0	0	0	DIGO ROAD	27	0	0	1
35	135	1	1	1	47	PRICEWATERHOUSE COPPERS	Private	1	0	1	1440000	3	1	0	1	0.5	100000	4	1	0	0	0	0	0	HAILE SELASSIE	8	0	0	1
36	136	1	1	1	31	GLAXO WELLCOME (K) LTD	Private	1	1	1	387000	1	1	0	1	0.2	100000	4	0	0	0	0	0	0	AIRPORT	28	0	0	1
37	137	1	1	1	45	E A STORAGE CO LTD	Private	1	0	1	667200	2	1	0	1	0.2	101000	4	0	0	0	0	0	0	MARKET	9	0	0	1
38	138	1	1	1	33	ICL KENYA LTD	Private	1	0	1	720000	2	1	0	1	0.1	116000	4	0	0	0	0	0	0	MARKET	9	0	0	1
39	139	1	1	1	44	SELF EMPLOYED	Self	3	0	1	600000	2	1	1	1	0.1	82000	3	2	0	0	0	0	0	NKRUMAH ROAD	10	0	0	1
40	140	1	1	1	28	CHAVDA DITEN DINU	Private	1	0	1	240000	1	1	0	3	0.1	40000	1	2	3	0.05	0	1	0	KAKAMEGA	29	1	0	1
41	141	1	1	1	38	MOTOR MART LTD/YAMAHA MOTORS	Private	1	1	1	869316	3	1	0	1	0.1	66000	2	3	0	0	0	0	0	WESTLANDS	6	1	0	1
42	142	1	1	1	49	280 INVESTMENTS LTD	Private	1	1	1	600000	2	1	0	1	1	100000	4	5	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
43	143	1	1	1	34	FREELANCE ACCOUNTANTS	Private	1	1	1	450000	1	0	1	1	0.1	80000	3	8	0	0	0	0	0	ENTERPRISE RD	13	0	0	1
44	144	1	1	1	37	MOTOR MART	Private	1	1	1	1080000	3	0	1	1	0.1	86000	3	6	0	0	0	0	0	WESTLANDS	6	1	10	4
45	145	1	1	0	35	GERMAN SCHOOL SOCIETY	Private	1	1	1	1108152	3	1	1	2	0.2	66000	2	3	1	0	0	0	0	MOI AVENUE	23	1	0	1
46	146	1	1	1	37	CENTRAL BANK OF KENYA	Bank	8	1	1	1740000	4	1	2	1	0.6	82000	3	3	0	0	0	0	0	MOI AVENUE	23	1	0	1
47	147	1	1	1	35	KAPLAN & STRATTON	Private	1	1	1	1680000	4	1	0	1	0.3	45000	1	3	1	0	0	0	0	WESTLANDS	6	1	2	3
48	148	1	1	1	40	GENERAL MOTORS KENYA	Private	1	1	1	1698000	4	1	0	1	0.3	91000	3	2	0	0	0	0	0	KAREN	11	1	0	1
49	149	1	1	1	36	ICRAF	Private	1	1	1	1106916	3	1	1	1	0.2	43000	1	2	0	0	0	0	0	WESTLANDS	6	1	0	1
50	150	1	1	1	31	CO-OP BANK	Bank	8	1	1	900000	3	0	0	1	0.2	100000	4	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
51	151	1	1	1	37	NAIROBI UNIVERSITY	Para	4	1	1	420000	1	1	0	1	0.2	70000	2	6	0	0.02	0	1	0	QUEENSWAY	5	1	0	1
52	152	1	1	1	48	MOBILE 072-746147	None		1	1	1561020	4	1	2	1	0.2	86000	3	1	0	0	0	0	0	QUEENSWAY	5	1	0	1
53	153	1	1	1	43	TOP SPEED FREIGHT FORW LTD	Private	1	1	1	525720	1	1	1	1	0.1	120000	4	1	0	0	0	0	0	WESTLANDS	6	1	0	1
54	154	1	1	1	35	ARCHDIOCESE OF NAIROBI	Private	1	1	1	100000	1	0	1	1	0.1	66000	2	1	2	0	0	0	0	AIRPORT	28	1	0	1
55	155	1	1	1	36	UNGA GROUP LTD	Private	1	1	1	1503840	4	1	0	1	0.1	45000	1	1	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
56	156	1	1	1	39	SABIL KENYA	Private	1	0	1	720000	2	1	0	1	0.1	53000	1	0	0	0	0	0	0	QUEENSWAY	5	1	0	1
57	157	1	1	1	33	KENYA SHELL LTD	Private	1	1	1	930900	3	1	0	2	0.1	100000	4	3	0	0	0	0	0	AIRPORT	28	1	0	1
58	158	1	1	1	47	IPPF;AFRICA REGION	Private	1	1	1	2367351	4	0	0	1	0.1	86000	3	3	0	0	0	0	0	AIRPORT	28	1	0	1
59	159	1	1	1	53	AFRICA ALLIANCE OF YMCA	Private	1	1	1	1200000	3	0	0	1	0.1	100000	4	3	0	0	0	0	0	AIRPORT	28	0	0	1
60	160	1	1	1	42	HAMILTON HARRISON & MA	Private	1	1	1	960000	3	1	0	1	0.2	150000	4	2	0	0	0	0	0	MARKET	9	1	0	1

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
61	161	1	1	1	49	MUKIRI & COMPANY	Self	3	1	1	1000000	3	1	0	1	1	250000	4	5	0	0	0	0	1	WESTLANDS	6	1	0	1
62	162	1	1	0	29	MANUFACTURING & CONSULTANCY	Private	1	1	1	600000	2	1	2	1	0.1	38000	1	1	0	0	0	0	0	MARKET	9	1	0	1
63	163	1	1	1	45	TSUBIS LTD	Private	1	1	1	3000000	4	1	2	1	0.1	100000	4	1	0	0	0	0	0	MARKET	9	0	0	1
64	164	1	1	1	35	EXPORT PROMOTION COUNCIL	Para	4	1	1	789000	3	1	2	2	0.2	48000	1	0	0	0	0	0	0	RAHIMTULLA PRESTIGE	30	0	0	1
65	165	1	1	1	38	SEMBHI ENTERPRISES	Private	1	0	1	256000	1	1	1	1	0.5	50000	1	1	0	0	0	0	0	NYERI	31	1	0	1
66	166	1	1	1	34	TWIGA CHEMICAL IND. LTD	Private	1	1	1	758340	3	1	0	1	0.1	56000	2	1	0	0	0	0	0	PLAZA	32	1	0	1
67	167	1	1	0	30	ORGANISATION OF AFRICA UNITY	Inter	6	0	1	780000	3	1	0	1	0.1	100000	4	3	0	0	0	2	0	LAVINGTON	33	1	30	5
68	168	1	1	1	41	STANDARD CHARTERED BANK	Bank	8	1	1	1800000	4	0	3	1	0.8	100000	4	1	0	0	0	0	0	HURLINGHAM	7	1	0	1
69	169	1	1	1	36	MOSAL CLEANING ENTERPRISE	Private	1	0	1	4000000	4	1	0	4	0.5	66000	2	1	0	0	0	0	0	MERU	22	1	0	1
70	170	1	1	0	30	CPC (K) LTD	Private	1	1	1	700000	2	1	0	1	0.1	66000	2	4	0	0	0	0	0	QUEENSWAY	5	1	0	1
71	171	1	1	1	37	NAIROBI CITY COUNCIL	Para	4	1	1	491400	1	1	0	1	0.1	86000	3	4	1	0	0	0	0	QUEENSWAY	5	0	0	1
72	172	1	1	1	33	KENYA BREWERIES	Private	1	1	1	1032000	3	1	1	1	0.1	30000	1	6	0	0	0	0	0	QUEENSWAY	5	1	0	1
73	173	1	0	0	28	TSC	Gov	2	1	1	600000	2	1	0	1	0.1	76000	3	8	0	0	0	0	0	QUEENSWAY	5	1	0	1
74	174	1	1	1	35	KENYA BREWERIES LTD	Private	1	1	1	1325760	3	0	0	1	0.4	86000	3	2	0	0	0	0	0	MARKET	9	1	0	1
75	175	1	1	1	33	KAGIO ESSO SERVICE STATION	Private	1	0	1	720000	2	1	0	1	0.1	40000	1	2	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
76	176	1	1	1	40	DATOO ASS.	Private	1	0	1	1800000	4	0	0	3	0.1	50000	1	1	0	0	0	0	0	WESTLANDS	6	1	0	1
77	177	1	1	1	38	WORLD BANK/NARP	Inter	6	1	1	3960000	4	1	3	3	0.2	100000	4	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
78	178	1	1	1	36	GEMINI STORES	Private	1	1	1	1440000	3	1	1	4	0.5	130000	4	1	0	0.12	0	1	0	ENTERPRISE RD	13	1	3	3
79	179	1	1	1	37	EATEC LTD	Private	1	1	1	2023560	4	1	0	1	0.2	96000	4	1	1	0	0	0	0	ENTERPRISE RD	13	0	0	1
80	180	1	1	1	41	KENYA PIPELINE CO. LTD	Para	4	0	1	1000000	3	1	0	1	0.1	50000	1	0	0	0	0	0	0	WUNDANYI	34	1	0	1
81	181	1	1	1	33	HERITAGE INSURANCE CO	Private	1	1	1	691932	2	1	0	1	0.1	40000	1	0	0	0	0	0	0	RUARAKA	19	1	0	1
82	182	1	1	0	31	TAR UNIVERSITY	Private	1	1	1	375240	1	1	0	1	0.1	60000	2	3	0	0	0	0	0	RUARAKA	19	1	0	1
83	183	1	1	1	45	UNITED TOURING CO. LTD	Private	1	0	1	648000	2	1	2	1	0.1	53000	1	2	0	0	0	0	0	MALINDI	35	0	0	1
84	184	1	1	1	41	KENYA BREWERIES LTD	Private	1	1	1	486120	1	0	0	1	0.1	50000	1	2	2	0	0	0	0	RUARAKA	17	0	0	1
85	185	1	1	1	33	KCB LTD	Bank	8	1	1	720000	2	0	2	1	0.6	100000	4	0	0	0	0	0	0	MUTHAIGA	7	0	0	1
86	186	1	1	0	33	COCA-COLA AFRICA LTD	Private	1	1	1	844800	3	1	2	1	0.1	66000	2	1	0	0	0	0	0	MUTHAIGA	7	1	0	1
87	187	1	1	1	36	FIRST ASSURANCE CO.LTD	Private	1	0	1	4200000	4	1	2	1	0.5	100000	4	3	0	0	0	0	0	NKRUMAH ROAD	10	1	20	5

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
88	188	1	1	0	34	BARCLAYS BANK	Bank	8	1	1	1197924	3	0	1	2	0.6	96000	4	3	0	0.005	0	0	0	RUARAKA	17	1	0	1
89	189	1	1	1	32	AON MINET INS. BROKERS LTD	Private	1	1	1	1038000	3	0	0	1	0.8	100000	4	3	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
90	190	1	1	1	36	C M C	Private	1	1	1	1440000	3	0	0	1	1	200000	4	3	0	0	0	0	1	ENTERPRISE RD	13	1	0	1
91	191	1	1	1	36	E.A.DEVELOPMENT BANK	Bank	8	1	1	806192	3	1	0	1	0.3	82000	3	3	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
92	192	1	1	1	45	PANESAR ENGINEERING ENT.	Private	1	0	1	1000000	3	1	0	1	0.1	66000	2	3	1	0	0	0	0	ELDORET	2	1	0	1
93	193	1	1	1	37	KIRUI CONSULTANTS	Private	1	1	1	750000	3	1	0	1	0.1	128000	4	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
94	194	1	1	1	48	PEMBE FLOUR MILLS	Private	1	1	1	1740000	4	1	2	2	0.1	66000	2	5	0	0	0	0	0	KAREN	11	1	0	1
95	195	1	1	0	41	UNICEF	Inter	6	1	1	1730730	4	1	0	2	0.8	66000	2	0	0	0	0	0	0	MUTHAIGA	7	1	0	1
96	196	1	1	1	32	MISS.COMM.OF ST PAUL	Inter	6	1	1	750000	3	1	0	1	0.1	66000	2	3	0	0	0	0	0	MUTHAIGA	7	1	0	1
97	197	1	1	1	38	JUDICIARY	Gov	2	0	1	563000	2	1	0	1	0.1	66000	2	2	0	0	0	0	0	NANYUKI	36	1	0	1
98	198	1	1	1	31	CITY X-RAY SERVICES	Private	1	1	1	812000	3	1	0	1	0.1	66000	2	2	0	0	0	0	0	QUEENSWAY	5	1	2	3
99	199	1	1	1	32	AMEDO	Private	1	1	1	1020000	3	0	1	1	0.2	80000	3	2	0	0	0	0	0	JKIA	28	1	0	1
100	200	1	1	1	33	AMEDO CENTRE (K) LTD	Private	1	1	1	1070640	3	1	0	1	0.1	100000	4	1	0	0	0	0	0	KAREN	11	1	0	1

Appendix 2 :Credit Card Coded Data All

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
1	1	0	1	1	35	BASFEA LTD	Private	1	0	1	1293700	3	1	3	2	0.25	150000	4	8	3	0.35	3	5	0	DIANI	1	1	90	7
3	3	0	0	1	31	TSC	Gov	2	1	1	490000	1	0	3	1	0.1	150000	4	3	3	0.5	5	3	0	QUEENSWAY	3	1	150	9
4	4	0	0	1	30	ZANCO AGENCIES	Private	1	0	1	960000	3	0	3	2	0.1	25000	1	2	3	0.5	5	3	0	KERICHO	4	0	150	9
5	5	0	1	1	38	DIAMOND MEDICAL SVCS	Private	1	1	1	1000000	3	0	2	0	0.1	150000	4	2	5	0.5	5	3	0	QUEENSWAY	5	1	150	9
6	6	0	1	1	42	SELF EMPLOYED	Self	3	1	1	790000	3	0	1	1	0.6	50000	1	2	3	0.5	5	6	0	QUEENSWAY	5	0	150	9
7	7	0	1	1	32	KENYA PIPELINE CO. LTD	Para	4	1	1	635448	2	0	1	0	0.2	50000	1	5	3	0.42	5	3	0	QUEENSWAY	5	0	150	9
8	8	0	1	1	32	EAST AFRICAN CONFERENCE	Private	1	1	1	3078000	4	1	1	3	0.2	300000	4	5	4	0.55	3	2	1	WESTLANDS	6	0	90	7
9	9	0	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	760000	3	0	1	3	0.2	100000	4	5	8	0.3	3	4	0	QUEENSWAY	5	0	90	7
10	10	0	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	1250000	3	0	4	3	0.2	140000	4	12	8	1.1	3	4	0	MUTHAIGA	7	0	90	7
11	11	0	1	1	38	KTDA	Para	4	0	1	1678812	4	1	1	3	0.5	130000	4	6	8	0.42	4	4	0	WESTLANDS	6	0	120	8
12	12	0	1	1	46	INFINITY ADVERTISING	Private	1	1	1	300000	1	1	2	2	1	65000	2	5	6	0.48	4	4	0	HAILE SELLASIE	8	0	120	8
13	13	0	1	1	42	INDONESIAN EMBASSY	Inter	6	1	0	3480000	4	1	2	1	0.8	70000	2	5	3	0.48	4	4	0	MARKET	9	0	120	8
14	14	0	0	1	28	THEMIS INVESTMENTS LTD.	Private	1	1	1	1968000	4	1	2	1	0.3	100000	4	2	3	0.51	4	4	0	MARKET	9	1	120	8
15	15	0	0	1	30	SATEL ENGINEERS	Private	1	1	1	1200000	3	1	1	1	0.3	80000	3	1	3	0.34	8	4	0	QUEENSWAY	5	1	240	11
16	16	0	1	1	35	RETIRED	Retired	7	0	1	475000	1	1	1	5	0.6	128000	4	7	3	0.41	8	4	0	NKRUMAH RD	10	1	240	11
17	17	0	1	1	33	TELCOM	Para	4	1	1	750000	3	1	1	2	0.1	50000	1	3	3	0.33	9	3	0	KAREN	11	1	270	11
18	18	0	0	1	32	KTDA	Para	4	1	1	1104000	3	0	1	1	0.1	50000	1	3	3	0.4	8	2	0	HURLINHAM	7	1	240	11
19	19	0	1	1	32	MARSHALLS E.A. LTD	Private	1	0	1	600000	2	1	3	1	0.1	50000	1	3	7	0.65	8	5	0	KAKAMEGA	12	0	24	5
20	20	0	0	1	32	TELCOM	Para	4	0	1	316000	1	1	1	1	0.1	50000	1	3	9	0.3	8	6	0	NKRUMAH RD	10	0	240	11
21	21	0	1	1	39	KENYA ARMED FORCES	Forces	5	1	1	360000	1	0	4	1	1	100000	4	2	9	0.3	5	6	0	QUEENSWAY	5	0	150	9
22	22	0	1	1	43	KENYA PIPELINE CO. LTD	Para	4	1	1	780000	3	0	4	0	1	70000	2	8	9	0.44	5	6	0	QUEENSWAY	5	1	150	9
23	23	0	0	1	32	KENYA UTALII COLLEGE	Para	4	1	1	500000	1	0	3	3	0.2	50000	1	10	12	0.8	5	6	0	QUEENSWAY	5	0	150	9
24	24	0	1	1	35	TELCOM	Para	4	1	1	500000	1	0	1	3	1	80000	3	4	5	0.75	6	5	0	ENTERPRISE ROAD	13	0	180	10
25	25	0	1	1	40	TELCOM	Para	4	1	1	1904000	4	0	2	3	1	66000	2	3	5	0.6	3	4	0	QUEENSWAY	5	0	90	7
2	26	0	1	1	42	AERO SUPPORT LTD	Private	1	0	1	600000	2	0	3	4	0.1	70000	2	12	3	0.67	8	3	0	ELDORET	2	1	90	7

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreasC
26	26	0	1	1	46	SELF	Para	4	1	1	3150000	4	1	2	2	0.1	80000	3	3	6	0.46	6	3	0	WESTLANDS	6	0	180	10
27	27	0	1	1	36	KENYA ARMED FORCES	Forces	5	1	1	360000	1	1	2	1	0.1	80000	3	9	6	0.5	4	3	0	QUEENSWAY	5	1	120	8
28	28	0	1	1	36	KENYA PIPELINE CO. LTD	Forces	5	1	1	696000	2	1	3	1	0.1	50000	1	11	6	0.5	4	3	0	QUEENSWAY	5	0	120	8
29	29	0	1	1	41	SELF EMPLOYED	Self	3	1	1	2155200	4	0	2	1	0.8	100000	4	5	6	0.39	4	4	0	QUEENSWAY	5	0	120	8
30	30	0	1	1	39	SELF	Self	3	0	1	480000	1	0	2	1	0.8	25000	1	2	6	0.28	3	4	0	KISII	14	0	90	7
31	31	0	1	1	36	SELF	Self	3	1	1	389000	1	0	2	1	0.8	50000	1	2	6	0.3	3	4	0	MARKET	9	0	90	7
32	32	0	0	0	29	D.T.DOBIE	Private	1	1	1	528000	1	0	2	1	0.8	50000	1	2	12	0.3	3	3	0	PLAZA	15	0	90	7
33	33	0	0	1	33	AVENTIS CROPSCIENCE	Private	1	1	1	720000	2	0	3	1	0.6	50000	1	3	3	0.56	7	6	0	ENTERPRISE ROAD	13	0	210	10
34	34	0	1	1	39	DOD KENYA NAVY	Forces	5	0	1	772440	3	0	3	2	0.2	40000	1	6	8	0.77	6	6	0	NAKURU EAST	15	1	180	10
35	35	0	1	1	58	RETIRED	Retired	7	1	1	1470312	3	0	1	2	0.5	100000	4	7	8	0.36	6	5	0	QUEENSWAY	5	0	180	10
36	36	0	1	0	36	KASWA LTD	Private	1	1	1	720000	2	0	2	2	0.5	70000	2	7	8	0.49	6	5	0	QUEENSWAY	5	0	180	10
37	37	0	0	0	30	KENYA AIRWAYS	Private	1	1	1	1140000	3	0	2	2	0.5	50000	1	15	8	1.05	8	5	0	QUEENSWAY	5	0	240	11
38	38	0	1	1	35	KENYA POWER & LIGHTING	Private	1	1	1	1313968	3	0	2	2	0.5	70000	2	8	8	0.4	5	5	0	QUEENSWAY	5	1	150	9
39	39	0	1	1	35	KENYA BREWERIS LTD	Private	1	1	1	1657704	4	0	2	2	0.8	90000	3	5	8	0.4	5	5	0	QUEENSWAY	5	1	150	9
40	40	0	1	1	34	KENYA ARMED FORCES	Forces	5	1	1	862000	3	0	2	2	0.6	50000	1	5	10	0.45	7	5	0	QUEENSWAY	5	0	210	10
41	41	0	1	0	31	EAST END PLAZA NAIROBI WEST	Private	1	1	1	4680000	4	0	2	2	0.3	50000	1	5	4	0.75	5	3	0	QUEENSWAY	5	0	150	9
42	42	0	0	1	29	COMMERCIAL BANK OF AFRICA	Bank	8	0	1	887232	3	1	2	2	0.3	60000	2	5	7	0.6	3	3	0	WESTLANDS	6	0	90	7
43	43	0	1	1	42	EABS	Private	1	1	1	1081368	3	1	1	2	0.6	50000	1	9	12	0.9	8	5	0	WESTLANDS	6	0	240	11
44	44	0	1	1	40	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1424000	3	1	1	3	0.5	76000	3	13	5	0.95	9	5	0	WESTLANDS	6	0	270	11
45	45	0	1	1	38	K T D A	Para	4	0	1	1216020	3	1	1	2	0.4	50000	1	2	5	0.43	3	3	0	MERU	16	0	90	7
46	46	0	1	1	38	SELF-INTRA DELTA CO LTD	Private	1	1	1	1200000	3	0	2	3	0.1	30000	1	2	5	0.3	3	3	0	WESTLANDS	6	0	90	7
47	47	0	1	1	34	SELF	Self	3	1	1	3600000	4	0	3	3	0.1	90000	3	1	5	0.4	4	3	0	WESTLANDS	6	0	120	8
48	48	0	1	1	32	IMPALA GLASS IND LTD	Private	1	1	1	480000	1	1	2	3	0.2	80000	3	1	8	0.4	3	3	0	QUEENSWAY	5	0	90	7
49	49	0	1	1	45	SOTIK TEA COMPANY LTD	Private	1	0	1	1866000	4	1	1	2	0.2	40000	1	1	3	0.4	3	3	0	THIKA	17	0	90	7
50	50	0	1	1	43	ASK	Para	4	1	1	700000	2	1	4	2	0.2	160000	4	2	7	0.36	3	3	0	ENTERPRISE ROAD	13	0	90	7
51	51	0	1	0	38	ISRAEL AIRLINES LTD	Private	1	1	1	956000	3	1	1	2	0.2	50000	1	1	7	0.2	5	3	0	KAREN	11	1	150	9
52	52	0	1	1	46	SELF-MWEA MEDICAL CENTRE	Private	1	0	1	2000000	4	1	1	1	0.2	66000	2	1	7	0.25	2	4	0	EMBU	18	1	60	6

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
53	53	0	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	480000	1	1	2	4	1	30000	1	8	4	0.74	3	4	0	RUARAKA	19	1	90	7
54	54	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	731000	2	1	2	4	0.2	60000	2	12	7	0.92	3	3	0	NIC HSE	20	1	90	7
55	55	0	1	1	48	KENYA PIPELINE CO. LTD	Para	4	0	1	960000	3	1	2	1	1	50000	1	7	7	0.7	3	3	0	BUNGOMA	21	0	90	7
56	56	0	0	1	35	NYAGA NYAMU AND CO	Private	1	0	1	800000	3	0	1	0	1	66000	2	7	9	0.68	6	5	0	MERU	22	0	180	10
57	57	0	1	1	43	DOD	Forces	5	1	1	695188	2	0	3	0	0.6	30000	1	7	3	0.4	6	5	0	QUEENSWAY	5	1	180	10
58	58	0	0	1	35	DOD	Forces	5	1	1	1225160	3	0	2	0	0.6	70000	2	8	8	0.6	6	5	0	NIC HSE	20	0	180	10
59	59	0	1	1	38	UNIVERSITY OF NAIROBI	Para	4	1	1	750000	3	0	1	1	0.1	40000	1	6	8	0.6	4	5	0	QUEENSWAY	5	1	120	8
60	60	0	0	1	32	S D CONSTRUCTION LTD	Private	1	1	1	960000	3	0	1	4	0.1	100000	4	3	8	0.35	4	5	0	QUEENSWAY	5	1	120	8
61	61	0	1	1	38	DOD	Forces	5	1	1	2760000	4	1	3	6	0.1	100000	4	16	8	1.25	10	9	0	QUEENSWAY	5	0	300	11
62	62	0	0	1	34	KENYA BREWERIES LTD	Private	1	0	1	1611444	4	0	3	1	1	100000	4	2	9	0.2	3	2	0	WESTLANDS	6	0	90	7
63	63	0	1	1	34	AMOS AUTO GARAGE	Private	1	1	1	600000	2	0	1	0	0.75	100000	4	6	6	0.4	6	3	0	WESTLANDS	6	0	180	10
64	64	0	1	1	38	DOD	Forces	5	1	1	810000	3	1	1	1	0.6	70000	2	4	6	0.4	6	4	0	MOI AVENUE	23	0	180	10
65	65	0	1	1	36	SULMAC CO LTD	Private	1	1	1	1188000	3	0	2	2	0.5	100000	4	3	6	0.28	3	3	0	MOI AVENUE	23	1	90	7
66	66	0	1	1	41	DOD	Forces	5	1	1	720000	2	0	2	2	0.6	40000	1	3	6	0.25	3	3	0	MOI AVENUE	23	1	90	7
67	67	0	0	1	30	BEATMAN AND BATON LTD	Private	1	1	1	1360000	3	0	2	2	0.5	70000	2	3	4	0.3	3	3	0	MUTHAIGA	7	1	90	7
68	68	0	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	1373060	3	0	1	2	0.5	60000	2	3	11	0.3	3	3	0	MUTHAIGA	7	1	90	7
69	69	0	1	1	42	SELF EMPLOYED	Self	3	1	1	898000	3	0	1	2	0.5	130000	4	8	8	0.62	4	4	0	MOI AVENUE	23	1	120	8
70	70	0	1	1	34	N S S F	Para	4	1	1	1043160	3	0	1	2	0.5	40000	1	11	8	0.93	7	6	0	WESTLANDS	6	1	210	10
71	71	0	0	0	32	TSC	Gov	2	1	1	780000	3	0	1	3	0.75	50000	1	7	3	0.44	3	3	0	MOI AVENUE	23	0	90	7
72	72	0	1	1	35	KENYA BOOM TRADERS	Private	1	1	1	690000	2	0	3	3	0.25	128000	4	6	4	0.45	5	3	0	MOI AVENUE	23	1	150	9
73	73	0	0	1	29	TRANSNATIONAL BANK	Bank	8	1	1	1414200	3	1	3	2	0.25	40000	1	3	4	0.3	3	3	0	QUEENSWAY	5	1	90	7
74	74	0	0	1	33	TRANSAMI KENYA LTD	Private	1	1	1	1128000	3	0	3	4	0.2	66000	2	6	3	0.75	6	5	0	MOI AVENUE	23	0	180	10
75	75	0	1	1	43	KENYA ANTI CORRUPTION COMMISSION	Para	4	0	1	620000	2	0	3	1	0.25	128000	4	6	9	0.75	6	5	0	KISII	14	0	180	10
76	76	0	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1200000	3	1	4	1	0.75	120000	4	6	6	0.65	5	5	0	QUEENSWAY	5	0	150	9
77	77	0	1	1	37	KENYA POWER & LIGHTING	Para	4	1	1	1200000	3	1	1	1	0.3	100000	4	2	6	0.3	3	4	0	MOI AVENUE	23	0	90	7
78	78	0	1	1	48	KUTUS AUTO H/WARE LTD	Private	1	0	1	480000	1	1	2	0	0.3	50000	1	2	6	0.31	3	3	0	KERUGOYA	24	0	90	7
79	79	0	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	614960	2	1	2	3	0.4	100000	4	5	6	0.5	4	3	0	MOI AVENUE	23	0	120	8

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
80	80	0	1	1	42	KENYA AIRPORTS AUTHORITY	Para	4	0	1	1200000	3	0	1	3	0.1	50000	1	5	6	0.45	3	3	0	BUNGOMA	21	0	90	7
81	81	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	468000	1	1	3	3	0.1	80000	3	10	4	0.86	8	6	0	MOI AVENUE	23	0	240	11
82	82	0	1	1	36	CENTRAL BANK OF KENYA	Bank	8	1	1	3110205	4	0	1	2	0.1	240000	4	6	6	0.6	4	3	1	MOI AVENUE	23	0	120	8
83	83	0	1	1	28	COCA COLA NORTHERN AFRICA	Private	1	1	1	960000	3	0	1	2	0.8	96000	4	5	6	0.6	4	3	0	WESTLANDS	6	0	120	8
84	84	0	0	1	31	B A T [K] LTD	Private	1	1	1	960000	3	0	1	1	0.6	50000	1	5	6	0.62	5	4	0	MOI AVENUE	23	1	150	9
85	85	0	0	0	28	ROYAL INSURANCE OF E.A.	Private	1	1	1	1800000	4	0	1	1	0.6	100000	4	5	3	0.47	4	4	0	QUEENSWAY	5	0	120	8
86	86	0	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	219600	1	0	1	2	0.5	60000	2	6	3	0.7	6	4	0	QUEENSWAY	5	0	180	10
87	87	0	0	1	30	DEL-MONTE [K] LTD	Private	1	1	1	2028480	4	0	1	2	0.5	50000	1	4	3	0.4	3	4	0	QUEENSWAY	5	0	90	7
88	88	0	1	1	42	KENYA PORTS AUTHORITY	Para	4	0	1	1521720	4	0	2	2	0.8	86000	3	1	7	0.35	2	3	0	NKRUMAH RD	10	0	60	6
89	89	0	1	1	37	KENYA AIRPORTS AUTHORITY	Para	4	0	1	485000	1	0	2	2	0.8	50000	1	8	4	0.75	6	6	0	NKRUMAH RD	10	1	180	10
90	90	0	0	1	33	TSC	Gov	2	1	1	665000	2	0	2	2	1	182000	4	12	8	0.8	6	5	0	MARKET	9	1	180	10
91	91	0	1	1	35	TSC	Gov	2	1	1	1255200	3	0	3	2	1	75000	3	4	3	0.5	5	5	0	MOI AVENUE	23	1	150	9
92	92	0	0	1	28	SAVAGE PARADISE LTD	Private	1	1	1	540000	1	0	1	2	0.75	50000	1	5	5	0.55	3	4	0	QUEENSWAY	5	1	90	7
93	93	0	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	1176000	3	0	1	2	0.6	50000	1	5	5	0.4	4	4	0	MOI AVENUE	23	1	120	8
94	94	0	0	1	34	TRADE WINGS INTERNATIONAL LTD	Private	1	1	1	1500000	4	0	4	2	0.75	76000	3	14	5	0.9	9	10	0	HAILE SELLASIE	8	0	270	11
95	95	0	1	0	35	STANDARD BANK(EX-STAFF)	Bank	8	1	1	1920000	4	1	1	2	0.8	100000	4	6	11	0.75	6	8	0	HAILE SELLASIE	8	0	180	10
96	96	0	1	1	42	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	296000	1	0	1	1	1	200000	4	3	6	0.39	4	5	0	RUARAKA	19	0	120	8
97	97	0	1	1	56	POSHO MILL	Private	1	0	1	226000	1	0	1	3	1	66000	2	3	6	0.6	4	5	0	NYAHURURU	25	0	120	8
98	98	0	1	1	38	KENYA POWER & LIGHTING	Para	4	1	1	315000	1	0	2	3	0.1	60000	2	2	6	0.55	4	4	0	MOI AVENUE	23	0	120	8
99	99	0	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	600000	2	1	2	4	0.1	70000	2	9	3	0.37	3	4	0	QUEENSWAY	5	0	90	7
100	100	0	0	1	29	STANDARD CHARTERED	Bank	8	1	1	2068560	4	0	2	1	0.8	80000	3	11	8	0.88	7	8	0	WESTLANDS	6	0	210	10
1	101	1	1	1	46	ABBEY INVESTMENTS LTD	Private	1	1	1	623000	2	0	1	1	0.2	195000	4	2	0	0	0	0	0	WESTLANDS	6	0	0	1
2	102	1	1	1	52	SHAH MUNGE & PARTNERS LTD	Private	1	1	1	480000	1	1	0	1	0.5	150000	4	1	0	0	0	0	0	QUEENSWAY	5	0	0	1
3	103	1	1	1	42	EAST AFRICAN CEMENT	Private	1	1	1	615000	2	0	0	1	0.1	96000	4	3	0	0	0	0	0	QUEENSWAY	5	1	0	1
4	104	1	1	1	59	NAIROBI CITY COUNCIL	Para	4	1	1	380000	1	1	0	1	0.1	66000	2	3	1	0.02	0	0	0	QUEENSWAY	5	0	0	1
5	105	1	1	1	54	GENERAL ACCIDENT INSURANCE CO.	Private	1	1	1	750000	3	1	2	1	0.2	100000	4	5	0	0	0	0	0	QUEENSWAY	5	1	2	3
6	106	1	1	1	47	MITSUBISHI CORPORATION	Private	1	1	1	727200	2	1	1	1	0.3	150000	4	0	0	0	0	0	0	QUEENSWAY	5	1	0	1

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPlArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
7	107	1	1	1	49	FIRESTONE [E.A] 1969 LTD	Private	1	0	1	480000	1	0	2	1	0.5	66000	2	0	0	0	0	0	0	NKRUMAH ROAD	10	0	0	1
8	108	1	1	1	35	FIRESTONE E.A.(1969)LTD	Private	1	1	1	400000	1	0	2	1	0.1	50000	1	1	0	0	0	0	0	HURLINGHAM	7	0	0	1
9	109	1	1	1	45	GREENSTATES SCHOOL	Private	1	0	1	840000	3	1	1	2	0.1	66000	2	2	0	0	0	0	0	THIKA	17	1	8	3
10	110	1	1	1	42	KENYA POWER & LIGHTING CO.LTD	Para	4	1	1	648000	2	1	0	1	0.1	91000	3	2	0	0	0	0	0	WESTLANDS	6	1	1	2
11	111	1	1	1	48	COOPERS & LYBRAND	Private	1	1	1	996000	3	1	0	1	1	50000	1	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
12	112	1	1	1	36	VICTORIA COMMERCIAL BANK	Bank	8	1	1	700200	2	1	0	1	0.8	100000	4	2	0	0	0	0	0	MARKET	9	1	0	1
13	113	1	1	1	42	CONSTRUCTION PROJECT CONSULTAN	Private	1	0	1	727560	2	0	0	1	0.3	50000	1	6	0	0	0	0	0	KITALE	26	1	0	1
14	114	1	1	1	45	KENYA POWER & LIGHTING CO.LTD	Private	1	1	1	840000	3	1	0	1	0.1	200000	4	3	0	0	0	0	1	ENTERPRISE RD	13	1	0	1
15	115	1	1	0	39	GLAXO WELLCOME (K) LTD	Private	1	1	1	600000	2	0	2	1	0.1	50000	1	3	0	0	0	0	0	WESTLANDS	6	1	0	1
16	116	1	0	1	33	MICRO REGISTRARS LTD	Private	1	1	1	1124000	3	1	0	1	0.1	75000	3	2	0	0	0	0	0	MARKET	9	1	0	1
17	117	1	1	0	40	SELF EMPLOYED (GR COLLECTIONS)	Self	3	1	1	690192	2	1	3	1	0.2	200000	4	2	0	0	0	0	1	QUEENSWAY	5	0	0	1
18	118	1	1	1	31	CUSSONS	Private	1	1	1	720000	2	0	1	1	0.1	100000	4	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
19	119	1	0	0	28	AIRLINK LTD	Private	1	1	1	372000	1	1	0	1	0.1	76000	3	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
20	120	1	1	1	44	MIGITI ENTERPRISES LTD	Private	1	1	1	720000	2	1	0	1	0.1	92000	3	1	0	0	0	0	0	KAREN	11	1	0	1
21	121	1	1	0	32	I.C.A.O	Private	1	1	1	456000	1	1	0	2	0.5	128000	4	1	1	0.1	0	1	0	WESTLANDS	6	1	12	4
22	122	1	1	1	29	YAKO LTD	Private	1	0	1	96000	1	1	0	2	0.1	50000	1	1	0	0	0	0	0	NAKURU EAST	15	1	0	1
23	123	1	1	1	36	BAT (K) LTD	Private	1	1	1	589000	2	1	0	1	1.1	40000	1	0	0	0	0	0	0	HURLINGHAM	7	1	0	1
24	124	1	1	1	33	DEL MONTE KENYA LTD	Private	1	0	0	1046964	3	0	0	1	0.5	150000	4	5	0	0	0	0	0	THIKA	17	1	0	1
25	125	1	1	1	42	BHOGAL'S GARAGE LTD	Private	1	0	1	3000000	4	1	0	1	0.1	66000	2	1	0	0	0	0	0	MOI AVENUE	23	1	0	1
26	126	1	1	1	38	PFIZER LABS	Private	1	1	1	900000	3	1	0	1	0.1	50000	1	1	0	0	0	0	0	MOI AVENUE	23	0	1	2
27	127	1	1	1	38	CARNAUDMETAL BOX K LTD	Private	1	1	1	1399200	3	1	0	1	0.1	96000	4	2	0	0	0	0	0	MOI AVENUE	23	0	0	1
28	128	1	1	1	32	M PINNACLE ENG/HARD WARE	Private	1	1	1	1400000	3	1	1	1	0.2	60000	2	4	0	0	0	0	0	MOI AVENUE	23	0	0	1
29	129	1	1	1	41	FINERALF FOREX BUREAU	Private	1	1	1	1200000	3	0	0	1	0.1	150000	4	6	0	0	0	0	0	MOI AVENUE	23	0	0	1
30	130	1	1	1	46	BARKER & BARTON (K) LTD	Private	1	1	1	1000000	3	1	2	1	0.3	86000	3	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
31	131	1	1	1	37	DYER AND BLAIR LTD	Private	1	1	1	1020000	3	1	2	1	0.1	81000	3	2	0	0	0	0	0	MARKET	9	0	0	1
32	132	1	1	1	39	LIVINGSTONE REGISTRARS LTD	Private	1	1	1	1260000	3	1	1	1	0.1	66000	2	2	0	0	0	0	0	MARKET	9	0	0	1
33	133	1	1	1	41	AKIBA BANK LTD	Bank	8	1	1	1140000	3	1	0	1	0.1	86000	3	2	0	0	0	1	0	MARKET	9	0	5	3

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
34	134	1	0	1	30	ABERCROMBIE & KENT [COAST] LTD	Private	1	0	1	330000	1	1	0	1	0.1	70000	2	2	0	0	0	0	0	DIGO ROAD	27	0	0	1
35	135	1	1	1	47	PRICEWATERHOUSE COPPERS	Private	1	0	1	1440000	3	1	0	1	0.5	100000	4	1	0	0	0	0	0	HAILE SELASSIE	8	0	0	1
36	136	1	1	1	31	GLAXO WELLCOME (K) LTD	Private	1	1	1	387000	1	1	0	1	0.2	100000	4	0	0	0	0	0	0	AIRPORT	28	0	0	1
37	137	1	1	1	45	E A STORAGE CO LTD	Private	1	0	1	667200	2	1	0	1	0.2	101000	4	0	0	0	0	0	0	MARKET	9	0	0	1
38	138	1	1	1	33	ICL KENYA LTD	Private	1	0	1	720000	2	1	0	1	0.1	116000	4	0	0	0	0	0	0	MARKET	9	0	0	1
39	139	1	1	1	44	SELF EMPLOYED	Self	3	0	1	600000	2	1	1	1	0.1	82000	3	2	0	0	0	0	0	NKRUMAH ROAD	10	0	0	1
40	140	1	1	1	28	CHAVDA DITEN DINU	Private	1	0	1	240000	1	1	0	3	0.1	40000	1	2	3	0.05	0	1	0	KAKAMEGA	29	1	0	1
41	141	1	1	1	38	MOTOR MART LTD/YAMAHA MOTORS	Private	1	1	1	869316	3	1	0	1	0.1	66000	2	3	0	0	0	0	0	WESTLANDS	6	1	0	1
42	142	1	1	1	49	280 INVESTMENTS LTD	Private	1	1	1	600000	2	1	0	1	1	100000	4	5	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
43	143	1	1	1	34	FREELANCE ACCOUNTANTS	Private	1	1	1	450000	1	0	1	1	0.1	80000	3	8	0	0	0	0	0	ENTERPRISE RD	13	0	0	1
44	144	1	1	1	37	MOTOR MART	Private	1	1	1	1080000	3	0	1	1	0.1	86000	3	6	0	0	0	0	0	WESTLANDS	6	1	10	4
45	145	1	1	0	35	GERMAN SCHOOL SOCIETY	Private	1	1	1	1108152	3	1	1	2	0.2	66000	2	3	1	0	0	0	0	MOI AVENUE	23	1	0	1
46	146	1	1	1	37	CENTRAL BANK OF KENYA	Bank	8	1	1	1740000	4	1	2	1	0.6	82000	3	3	0	0	0	0	0	MOI AVENUE	23	1	0	1
47	147	1	1	1	35	KAPLAN & STRATTON	Private	1	1	1	1680000	4	1	0	1	0.3	45000	1	3	1	0	0	0	0	WESTLANDS	6	1	2	3
48	148	1	1	1	40	GENERAL MOTORS KENYA	Private	1	1	1	1698000	4	1	0	1	0.3	91000	3	2	0	0	0	0	0	KAREN	11	1	0	1
49	149	1	1	1	36	ICRAF	Private	1	1	1	1106916	3	1	1	1	0.2	43000	1	2	0	0	0	0	0	WESTLANDS	6	1	0	1
50	150	1	1	1	31	CO-OP BANK	Bank	8	1	1	900000	3	0	0	1	0.2	100000	4	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
51	151	1	1	1	37	NAIROBI UNIVERSITY	Para	4	1	1	420000	1	1	0	1	0.2	70000	2	6	0	0.02	0	1	0	QUEENSWAY	5	1	0	1
52	152	1	1	1	48	MOBILE 072-746147	None		1	1	1561020	4	1	2	1	0.2	86000	3	1	0	0	0	0	0	QUEENSWAY	5	1	0	1
53	153	1	1	1	43	TOP SPEED FREIGHT FORW LTD	Private	1	1	1	525720	1	1	1	1	0.1	120000	4	1	0	0	0	0	0	WESTLANDS	6	1	0	1
54	154	1	1	1	35	ARCHDIOCESE OF NAIROBI	Private	1	1	1	100000	1	0	1	1	0.1	66000	2	1	2	0	0	0	0	AIRPORT	28	1	0	1
55	155	1	1	1	36	UNGA GROUP LTD	Private	1	1	1	1503840	4	1	0	1	0.1	45000	1	1	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
56	156	1	1	1	39	SABIL KENYA	Private	1	0	1	720000	2	1	0	1	0.1	53000	1	0	0	0	0	0	0	QUEENSWAY	5	1	0	1
57	157	1	1	1	33	KENYA SHELL LTD	Private	1	1	1	930900	3	1	0	2	0.1	100000	4	3	0	0	0	0	0	AIRPORT	28	1	0	1
58	158	1	1	1	47	IPPF;AFRICA REGION	Private	1	1	1	2367351	4	0	0	1	0.1	86000	3	3	0	0	0	0	0	AIRPORT	28	1	0	1
59	159	1	1	1	53	AFRICA ALLIANCE OF YMCA	Private	1	1	1	1200000	3	0	0	1	0.1	100000	4	3	0	0	0	0	0	AIRPORT	28	0	0	1
60	160	1	1	1	42	HAMILTON HARRISON & MA	Private	1	1	1	960000	3	1	0	1	0.2	150000	4	2	0	0	0	0	0	MARKET	9	1	0	1

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
61	161	1	1	1	49	MUKIRI & COMPANY	Self	3	1	1	1000000	3	1	0	1	1	250000	4	5	0	0	0	0	1	WESTLANDS	6	1	0	1
62	162	1	1	0	29	MANUFACTURING & CONSULTANCY	Private	1	1	1	600000	2	1	2	1	0.1	38000	1	1	0	0	0	0	0	MARKET	9	1	0	1
63	163	1	1	1	45	TSUBIS LTD	Private	1	1	1	3000000	4	1	2	1	0.1	100000	4	1	0	0	0	0	0	MARKET	9	0	0	1
64	164	1	1	1	35	EXPORT PROMOTION COUNCIL	Para	4	1	1	789000	3	1	2	2	0.2	48000	1	0	0	0	0	0	0	RAHIMTULLA PRESTIGE	30	0	0	1
65	165	1	1	1	38	SEMBHI ENTERPRISES	Private	1	0	1	256000	1	1	1	1	0.5	50000	1	1	0	0	0	0	0	NYERI	31	1	0	1
66	166	1	1	1	34	TWIGA CHEMICAL IND. LTD	Private	1	1	1	758340	3	1	0	1	0.1	56000	2	1	0	0	0	0	0	PLAZA	32	1	0	1
67	167	1	1	0	30	ORGANISATION OF AFRICA UNITY	Inter	6	0	1	780000	3	1	0	1	0.1	100000	4	3	0	0	0	2	0	LAVINGTON	33	1	30	5
68	168	1	1	1	41	STANDARD CHARTERED BANK	Bank	8	1	1	1800000	4	0	3	1	0.8	100000	4	1	0	0	0	0	0	HURLINGHAM	7	1	0	1
69	169	1	1	1	36	MOSAL CLEANING ENTERPRISE	Private	1	0	1	4000000	4	1	0	4	0.5	66000	2	1	0	0	0	0	0	MERU	22	1	0	1
70	170	1	1	0	30	CPC (K) LTD	Private	1	1	1	700000	2	1	0	1	0.1	66000	2	4	0	0	0	0	0	QUEENSWAY	5	1	0	1
71	171	1	1	1	37	NAIROBI CITY COUNCIL	Para	4	1	1	491400	1	1	0	1	0.1	86000	3	4	1	0	0	0	0	QUEENSWAY	5	0	0	1
72	172	1	1	1	33	KENYA BREWERIES	Private	1	1	1	1032000	3	1	1	1	0.1	30000	1	6	0	0	0	0	0	QUEENSWAY	5	1	0	1
73	173	1	0	0	28	TSC	Gov	2	1	1	600000	2	1	0	1	0.1	76000	3	8	0	0	0	0	0	QUEENSWAY	5	1	0	1
74	174	1	1	1	35	KENYA BREWERIES LTD	Private	1	1	1	1325760	3	0	0	1	0.4	86000	3	2	0	0	0	0	0	MARKET	9	1	0	1
75	175	1	1	1	33	KAGIO ESSO SERVICE STATION	Private	1	0	1	720000	2	1	0	1	0.1	40000	1	2	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
76	176	1	1	1	40	DATOO ASS.	Private	1	0	1	1800000	4	0	0	3	0.1	50000	1	1	0	0	0	0	0	WESTLANDS	6	1	0	1
77	177	1	1	1	38	WORLD BANK/NARP	Inter	6	1	1	3960000	4	1	3	3	0.2	100000	4	1	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
78	178	1	1	1	36	GEMINI STORES	Private	1	1	1	1440000	3	1	1	4	0.5	130000	4	1	0	0.12	0	1	0	ENTERPRISE RD	13	1	3	3
79	179	1	1	1	37	EATEC LTD	Private	1	1	1	2023560	4	1	0	1	0.2	96000	4	1	1	0	0	0	0	ENTERPRISE RD	13	0	0	1
80	180	1	1	1	41	KENYA PIPELINE CO. LTD	Para	4	0	1	1000000	3	1	0	1	0.1	50000	1	0	0	0	0	0	0	WUNDANYI	34	1	0	1
81	181	1	1	1	33	HERITAGE INSURANCE CO	Private	1	1	1	691932	2	1	0	1	0.1	40000	1	0	0	0	0	0	0	RUARAKA	19	1	0	1
82	182	1	1	0	31	TAR UNIVERSITY	Private	1	1	1	375240	1	1	0	1	0.1	60000	2	3	0	0	0	0	0	RUARAKA	19	1	0	1
83	183	1	1	1	45	UNITED TOURING CO. LTD	Private	1	0	1	648000	2	1	2	1	0.1	53000	1	2	0	0	0	0	0	MALINDI	35	0	0	1
84	184	1	1	1	41	KENYA BREWERIES LTD	Private	1	1	1	486120	1	0	0	1	0.1	50000	1	2	2	0	0	0	0	RUARAKA	17	0	0	1
85	185	1	1	1	33	KCB LTD	Bank	8	1	1	720000	2	0	2	1	0.6	100000	4	0	0	0	0	0	0	MUTHAIGA	7	0	0	1
86	186	1	1	0	33	COCA-COLA AFRICA LTD	Private	1	1	1	844800	3	1	2	1	0.1	66000	2	1	0	0	0	0	0	MUTHAIGA	7	1	0	1
87	187	1	1	1	36	FIRST ASSURANCE CO.LTD	Private	1	0	1	4200000	4	1	2	1	0.5	100000	4	3	0	0	0	0	0	NKRUMAH ROAD	10	1	20	5

Case	CaseB	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas	LoArreaC
88	188	1	1	0	34	BARCLAYS BANK	Bank	8	1	1	1197924	3	0	1	2	0.6	96000	4	3	0	0.005	0	0	0	RUARAKA	17	1	0	1
89	189	1	1	1	32	AON MINET INS. BROKERS LTD	Private	1	1	1	1038000	3	0	0	1	0.8	100000	4	3	0	0	0	0	0	HAILE SELASSIE	8	1	0	1
90	190	1	1	1	36	C M C	Private	1	1	1	1440000	3	0	0	1	1	200000	4	3	0	0	0	0	1	ENTERPRISE RD	13	1	0	1
91	191	1	1	1	36	E.A.DEVELOPMENT BANK	Bank	8	1	1	806192	3	1	0	1	0.3	82000	3	3	0	0	0	0	0	ENTERPRISE RD	13	1	0	1
92	192	1	1	1	45	PANESAR ENGINEERING ENT.	Private	1	0	1	1000000	3	1	0	1	0.1	66000	2	3	1	0	0	0	0	ELDORET	2	1	0	1
93	193	1	1	1	37	KIRUI CONSULTANTS	Private	1	1	1	750000	3	1	0	1	0.1	128000	4	2	0	0	0	0	0	QUEENSWAY	5	1	0	1
94	194	1	1	1	48	PEMBE FLOUR MILLS	Private	1	1	1	1740000	4	1	2	2	0.1	66000	2	5	0	0	0	0	0	KAREN	11	1	0	1
95	195	1	1	0	41	UNICEF	Inter	6	1	1	1730730	4	1	0	2	0.8	66000	2	0	0	0	0	0	0	MUTHAIGA	7	1	0	1
96	196	1	1	1	32	MISS.COMM.OF ST PAUL	Inter	6	1	1	750000	3	1	0	1	0.1	66000	2	3	0	0	0	0	0	MUTHAIGA	7	1	0	1
97	197	1	1	1	38	JUDICIARY	Gov	2	0	1	563000	2	1	0	1	0.1	66000	2	2	0	0	0	0	0	NANYUKI	36	1	0	1
98	198	1	1	1	31	CITY X-RAY SERVICES	Private	1	1	1	812000	3	1	0	1	0.1	66000	2	2	0	0	0	0	0	QUEENSWAY	5	1	2	3
99	199	1	1	1	32	AMEDO	Private	1	1	1	1020000	3	0	1	1	0.2	80000	3	2	0	0	0	0	0	JKIA	28	1	0	1
100	200	1	1	1	33	AMEDO CENTRE (K) LTD	Private	1	1	1	1070640	3	1	0	1	0.1	100000	4	1	0	0	0	0	0	KAREN	11	1	0	1

Appendix 3 :Credit Card Coded Data Bad

Case	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas
1	1	1	35	BASFEA LTD	Private	1	0	1	1293700	4	1	3	2	0.25	150000	4	8	3	0.35	3	5	0	DIANI	1	1	90
2	1	1	42	AERO SUPPORT LTD	Private	1	0	1	600000	2	0	3	4	0.1	70000	3	12	3	0.67	8	3	0	ELDORET	2	1	90
3	0	1	31	TSC	Gov	2	1	1	490000	1	0	3	1	0.1	150000	4	3	3	0.5	5	3	0	QUEENSWAY	3	1	150
4	0	1	30	ZANCO AGENCIES	Private	1	0	1	960000	3	0	3	2	0.1	25000	1	2	3	0.5	5	3	0	KERICHO	4	0	150
5	1	1	38	DIAMOND MEDICAL SVCS	Private	1	1	1	1000000	4	0	2	0	0.1	150000	4	2	5	0.5	5	3	0	QUEENSWAY	5	1	150
6	1	1	42	SELF EMPLOYED	Self	3	1	1	790000	3	0	1	1	0.6	50000	2	2	3	0.5	5	6	0	QUEENSWAY	5	0	150
7	1	1	32	KENYA PIPELINE CO. LTD	Para	4	1	1	635448	2	0	1	0	0.2	50000	2	5	3	0.42	5	3	0	QUEENSWAY	5	0	150
8	1	1	32	EAST AFRICAN CONFERENCE	Private	1	1	1	3078000	4	1	1	3	0.2	300000	4	5	4	0.55	3	2	1	WESTLANDS	6	0	90
9	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	760000	3	0	1	3	0.2	100000	4	5	8	0.3	3	4	0	QUEENSWAY	5	0	90
10	0	1	32	KENYA ARMED FORCES	Forces	5	1	1	1250000	4	0	4	3	0.2	140000	4	12	8	1.1	3	4	0	MUTHAIGA	7	0	90
11	1	1	38	KTDA	Para	4	0	1	1678812	4	1	1	3	0.5	130000	4	6	8	0.42	4	4	0	WESTLANDS	6	0	120
12	1	1	46	INFINITY ADVERTISING	Private	1	1	1	300000	1	1	2	2	1	65000	2	5	6	0.48	4	4	0	HAILE SELLASIE	8	0	120
13	1	1	42	INDONESIAN EMBASSY	Embassy	6	1	0	3480000	4	1	2	1	0.8	70000	3	5	3	0.48	4	4	0	MARKET	9	0	120
14	0	1	28	THEMIS INVESTMENTS LTD.	Private	1	1	1	1968000	4	1	2	1	0.3	100000	4	2	3	0.51	4	4	0	MARKET	9	1	120
15	0	1	30	SATEL ENGINEERS	Private	1	1	1	1200000	4	1	1	1	0.3	80000	3	1	3	0.34	8	4	0	QUEENSWAY	5	1	240
16	1	1	35	RETIRED	Retired	7	0	1	475000	1	1	1	5	0.6	128000	4	7	3	0.41	8	4	0	NKRUMAH RD	10	1	240
17	1	1	33	TELCOM	Para	4	1	1	750000	3	1	1	2	0.1	50000	2	3	3	0.33	9	3	0	KAREN	11	1	270
18	0	1	32	KTDA	Para	4	1	1	1104000	4	0	1	1	0.1	50000	2	3	3	0.4	8	2	0	HURLINHAM	7	1	240
19	1	1	32	MARSHALLS E.A. LTD	Private	1	0	1	600000	2	1	3	1	0.1	50000	2	3	7	0.65	8	5	0	KAKAMEGA	12	0	24
20	0	1	32	TELCOM	Para	4	0	1	316000	1	1	1	1	0.1	50000	2	3	9	0.3	8	6	0	NKRUMAH RD	10	0	240
21	1	1	39	KENYA ARMED FORCES	Forces	5	1	1	360000	1	0	4	1	1	100000	4	2	9	0.3	5	6	0	QUEENSWAY	5	0	150
22	1	1	43	KENYA PIPELINE CO. LTD	Para	4	1	1	780000	3	0	4	0	1	70000	3	8	9	0.44	5	6	0	QUEENSWAY	5	1	150
23	0	1	32	KENYA UTALII COLLEGE	Para	4	1	1	500000	1	0	3	3	0.2	50000	2	10	12	0.8	5	6	0	QUEENSWAY	5	0	150
24	1	1	35	TELCOM	Para	4	1	1	500000	1	0	1	3	1	80000	3	4	5	0.75	6	5	0	ENTERPRISE ROAD	13	0	180
25	1	1	40	TELCOM	Para	4	1	1	1904000	4	0	2	3	1	66000	2	3	5	0.6	3	4	0	QUEENSWAY	5	0	90
26	1	1	46	SELF	Para	4	1	1	3150000	4	1	2	2	0.1	80000	3	3	6	0.46	6	3	0	WESTLANDS	6	0	180

Case	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas
27	1	1	36	KENYA ARMED FORCES	Forces	5	1	1	360000	1	1	2	1	0.1	80000	3	9	6	0.5	4	3	0	QUEENSWAY	5	1	120
28	1	1	36	KENYA PIPELINE CO. LTD	Forces	5	1	1	696000	2	1	3	1	0.1	50000	2	11	6	0.5	4	3	0	QUEENSWAY	5	0	120
29	1	1	41	SELF EMPLOYED	Self	3	1	1	2155200	4	0	2	1	0.8	100000	4	5	6	0.39	4	4	0	QUEENSWAY	5	0	120
30	1	1	39	SELF	Self	3	0	1	480000	1	0	2	1	0.8	25000	1	2	6	0.28	3	4	0	KISII	14	0	90
31	1	1	36	SELF	Self	3	1	1	389000	1	0	2	1	0.8	50000	2	2	6	0.3	3	4	0	MARKET	9	0	90
32	0	0	29	D.T.DOBIE	Private	1	1	1	528000	1	0	2	1	0.8	50000	2	2	12	0.3	3	3	0	PLAZA	15	0	90
33	0	1	33	AVENTIS CROPSCIENCE	Private	1	1	1	720000	2	0	3	1	0.6	50000	2	3	3	0.56	7	6	0	ENTERPRISE ROAD	13	0	210
34	1	1	39	DOD KENYA NAVY	Forces	5	0	1	772440	3	0	3	2	0.2	40000	1	6	8	0.77	6	6	0	NAKURU EAST	15	1	180
35	1	1	58	RETIRED	Retired	7	1	1	1470312	4	0	1	2	0.5	100000	4	7	8	0.36	6	5	0	QUEENSWAY	5	0	180
36	1	0	36	KASWA LTD	Private	1	1	1	720000	2	0	2	2	0.5	70000	3	7	8	0.49	6	5	0	QUEENSWAY	5	0	180
37	0	0	30	KENYA AIRWAYS	Private	1	1	1	1140000	4	0	2	2	0.5	50000	2	15	8	1.05	8	5	0	QUEENSWAY	5	0	240
38	1	1	35	KENYA POWER & LIGHTING	Private	1	1	1	1313968	4	0	2	2	0.5	70000	3	8	8	0.4	5	5	0	QUEENSWAY	5	1	150
39	1	1	35	KENYA BREWERIS LTD	Private	1	1	1	1657704	4	0	2	2	0.8	90000	3	5	8	0.4	5	5	0	QUEENSWAY	5	1	150
40	1	1	34	KENYA ARMED FORCES	Forces	5	1	1	862000	3	0	2	2	0.6	50000	2	5	10	0.45	7	5	0	QUEENSWAY	5	0	210
41	1	0	31	EAST END PLAZA NAIROBI WEST	Private	1	1	1	4680000	4	0	2	2	0.3	50000	2	5	4	0.75	5	3	0	QUEENSWAY	5	0	150
42	0	1	29	COMMERCIAL BANK OF AFRICA	Bank	8	0	1	887232	3	1	2	2	0.3	60000	2	5	7	0.6	3	3	0	WESTLANDS	6	0	90
43	1	1	42	EABS	Private	1	1	1	1081368	4	1	1	2	0.6	50000	2	9	12	0.9	8	5	0	WESTLANDS	6	0	240
44	1	1	40	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1424000	4	1	1	3	0.5	76000	3	13	5	0.95	9	5	0	WESTLANDS	6	0	270
45	1	1	38	K T D A	Para	4	0	1	1216020	4	1	1	2	0.4	50000	2	2	5	0.43	3	3	0	MERU	16	0	90
46	1	1	38	SELF-INTRA DELTA CO LTD	Private	1	1	1	1200000	4	0	2	3	0.1	30000	1	2	5	0.3	3	3	0	WESTLANDS	6	0	90
47	1	1	34	SELF	Self	3	1	1	3600000	4	0	3	3	0.1	90000	3	1	5	0.4	4	3	0	WESTLANDS	6	0	120
48	1	1	32	IMPALA GLASS IND LTD	Private	1	1	1	480000	1	1	2	3	0.2	80000	3	1	8	0.4	3	3	0	QUEENSWAY	5	0	90
49	1	1	45	SOTIK TEA COMPANY LTD	Private	1	0	1	1866000	4	1	1	2	0.2	40000	1	1	3	0.4	3	3	0	THIKA	17	0	90
50	1	1	43	ASK	Para	4	1	1	700000	2	1	4	2	0.2	160000	4	2	7	0.36	3	3	0	ENTERPRISE ROAD	13	0	90
51	1	0	38	ISRAEL AIRLINES LTD	Private	1	1	1	956000	3	1	1	2	0.2	50000	2	1	7	0.2	5	3	0	KAREN	11	1	150
52	1	1	46	SELF-MWEA MEDICAL CENTRE	Private	1	0	1	2000000	4	1	1	1	0.2	66000	2	1	7	0.25	2	4	0	EMBU	18	1	60
53	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	480000	1	1	2	4	1	30000	1	8	4	0.74	3	4	0	RUARAKA	19	1	90
54	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	731000	2	1	2	4	0.2	60000	2	12	7	0.92	3	3	0	NIC HSE	20	1	90

Case	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas
55	1	1	48	KENYA PIPELINE CO. LTD	Para	4	0	1	960000	3	1	2	1	1	50000	2	7	7	0.7	3	3	0	BUNGOMA	21	0	90
56	0	1	35	NYAGA NYAMU AND CO	Private	1	0	1	800000	3	0	1	0	1	66000	2	7	9	0.68	6	5	0	MERU	22	0	180
57	1	1	43	DOD	Forces	5	1	1	695188	2	0	3	0	0.6	30000	1	7	3	0.4	6	5	0	QUEENSWAY	5	1	180
58	0	1	35	DOD	Forces	5	1	1	1225160	4	0	2	0	0.6	70000	3	8	8	0.6	6	5	0	NIC HSE	20	0	180
59	1	1	38	UNIVERSITY OF NAIROBI	Para	4	1	1	750000	3	0	1	1	0.1	40000	1	6	8	0.6	4	5	0	QUEENSWAY	5	1	120
60	0	1	32	S D CONSTRUCTION LTD	Private	1	1	1	960000	3	0	1	4	0.1	100000	4	3	8	0.35	4	5	0	QUEENSWAY	5	1	120
61	1	1	38	DOD	Forces	5	1	1	2760000	4	1	3	6	0.1	100000	4	16	8	1.25	10	9	0	QUEENSWAY	5	0	300
62	0	1	34	KENYA BREWERIES LTD	Private	1	0	1	1611444	4	0	3	1	1	100000	4	2	9	0.2	3	2	0	WESTLANDS	6	0	90
63	1	1	34	AMOS AUTO GARAGE	Private	1	1	1	600000	2	0	1	0	0.75	100000	4	6	6	0.4	6	3	0	WESTLANDS	6	0	180
64	1	1	38	DOD	Forces	5	1	1	810000	3	1	1	1	0.6	70000	3	4	6	0.4	6	4	0	MOI AVENUE	23	0	180
65	1	1	36	SULMAC CO LTD	Private	1	1	1	1188000	4	0	2	2	0.5	100000	4	3	6	0.28	3	3	0	MOI AVENUE	23	1	90
66	1	1	41	DOD	Forces	5	1	1	720000	2	0	2	2	0.6	40000	1	3	6	0.25	3	3	0	MOI AVENUE	23	1	90
67	0	1	30	BEATMAN AND BATON LTD	Private	1	1	1	1360000	4	0	2	2	0.5	70000	3	3	4	0.3	3	3	0	MUTHAIGA	7	1	90
68	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	1373060	4	0	1	2	0.5	60000	2	3	11	0.3	3	3	0	MUTHAIGA	7	1	90
69	1	1	42	SELF EMPLOYED	Self	3	1	1	898000	3	0	1	2	0.5	130000	4	8	8	0.62	4	4	0	MOI AVENUE	23	1	120
70	1	1	34	N S S F	Para	4	1	1	1043160	4	0	1	2	0.5	40000	1	11	8	0.93	7	6	0	WESTLANDS	6	1	210
71	0	0	32	TSC	Gov	2	1	1	780000	3	0	1	3	0.75	50000	2	7	3	0.44	3	3	0	MOI AVENUE	23	0	90
72	1	1	35	KENYA BOOM TRADERS	Private	1	1	1	690000	2	0	3	3	0.25	128000	4	6	4	0.45	5	3	0	MOI AVENUE	23	1	150
73	0	1	29	TRANSNATIONAL BANK	Bank	8	1	1	1414200	4	1	3	2	0.25	40000	1	3	4	0.3	3	3	0	QUEENSWAY	5	1	90
74	0	1	33	TRANSAMI KENYA LTD	Private	1	1	1	1128000	4	0	3	4	0.2	66000	2	6	3	0.75	6	5	0	MOI AVENUE	23	0	180
75	1	1	43	KENYA ANTI CORRUPTION COMMISSION	Para	4	0	1	620000	2	0	3	1	0.25	128000	4	6	9	0.75	6	5	0	KISII	14	0	180
76	1	1	35	KENYA AIRPORTS AUTHORITY	Para	4	1	1	1200000	4	1	4	1	0.75	120000	4	6	6	0.65	5	5	0	QUEENSWAY	5	0	150
77	1	1	37	KENYA POWER & LIGHTING	Para	4	1	1	1200000	4	1	1	1	0.3	100000	4	2	6	0.3	3	4	0	MOI AVENUE	23	0	90
78	1	1	48	KUTUS AUTO H/WARE LTD	Private	1	0	1	480000	1	1	2	0	0.3	50000	2	2	6	0.31	3	3	0	KERUGOYA	24	0	90
79	1	1	40	KENYA POWER & LIGHTING	Para	4	1	1	614960	2	1	2	3	0.4	100000	4	5	6	0.5	4	3	0	MOI AVENUE	23	0	120
80	1	1	42	KENYA AIRPORTS AUTHORITY	Para	4	0	1	1200000	4	0	1	3	0.1	50000	2	5	6	0.45	3	3	0	BUNGOMA	21	0	90
81	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	468000	1	1	3	3	0.1	80000	3	10	4	0.86	8	6	0	MOI AVENUE	23	0	240
82	1	1	36	CENTRAL BANK OF KENYA	Bank	8	1	1	3110205	4	0	1	2	0.1	240000	4	6	6	0.6	4	3	1	MOI AVENUE	23	0	120

Case	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas
83	1	1	28	COCA COLA NORTHERN AFRICA	Private	1	1	1	960000	3	0	1	2	0.8	96000	3	5	6	0.6	4	3	0	WESTLANDS	6	0	120
84	0	1	31	B A T [K] LTD	Private	1	1	1	960000	3	0	1	1	0.6	50000	2	5	6	0.62	5	4	0	MOI AVENUE	23	1	150
85	0	0	28	ROYAL INSURANCE OF E.A.	Private	1	1	1	1800000	4	0	1	1	0.6	100000	4	5	3	0.47	4	4	0	QUEENSWAY	5	0	120
86	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	219600	1	0	1	2	0.5	60000	2	6	3	0.7	6	4	0	QUEENSWAY	5	0	180
87	0	1	30	DEL-MONTE [K] LTD	Private	1	1	1	2028480	4	0	1	2	0.5	50000	2	4	3	0.4	3	4	0	QUEENSWAY	5	0	90
88	1	1	42	KENYA PORTS AUTHORITY	Para	4	0	1	1521720	4	0	2	2	0.8	86000	3	1	7	0.35	2	3	0	NKRUMAH RD	10	0	60
89	1	1	37	KENYA AIRPORTS AUTHORITY	Para	4	0	1	485000	1	0	2	2	0.8	50000	2	8	4	0.75	6	6	0	NKRUMAH RD	10	1	180
90	0	1	33	TSC	Gov	2	1	1	665000	2	0	2	2	1	182000	4	12	8	0.8	6	5	0	MARKET	9	1	180
91	1	1	35	TSC	Gov	2	1	1	1255200	4	0	3	2	1	75000	3	4	3	0.5	5	5	0	MOI AVENUE	23	1	150
92	0	1	28	SAVAGE PARADISE LTD	Private	1	1	1	540000	1	0	1	2	0.75	50000	2	5	5	0.55	3	4	0	QUEENSWAY	5	1	90
93	0	1	30	STANDARD CHARTERED BANK	Bank	8	1	1	1176000	4	0	1	2	0.6	50000	2	5	5	0.4	4	4	0	MOI AVENUE	23	1	120
94	0	1	34	TRADE WINGS INTERNATIONAL LTD	Private	1	1	1	1500000	4	0	4	2	0.75	76000	3	14	5	0.9	9	10	0	HAILE SELLASIE	8	0	270
95	1	0	35	STANDARD BANK(EX-STAFF)	Bank	8	1	1	1920000	4	1	1	2	0.8	100000	4	6	11	0.75	6	8	0	HAILE SELLASIE	8	0	180
96	1	1	42	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	296000	1	0	1	1	1	200000	4	3	6	0.39	4	5	0	RUARAKA	19	0	120
97	1	1	56	POSHO MILL	Private	1	0	1	226000	1	0	1	3	1	66000	2	3	6	0.6	4	5	0	NYAHURURU	25	0	120
98	1	1	38	KENYA POWER & LIGHTING	Para	4	1	1	315000	1	0	2	3	0.1	60000	2	2	6	0.55	4	4	0	MOI AVENUE	23	0	120
99	1	1	40	MINISTRY OF PUBLIC WORKS	Gov	2	1	1	600000	2	1	2	4	0.1	70000	3	9	3	0.37	3	4	0	QUEENSWAY	5	0	90
100	0	1	29	STANDARD CHARTERED	Bank	8	1	1	2068560	4	0	2	1	0.8	80000	3	11	8	0.88	7	8	0	WESTLANDS	6	0	210

Appendix 4 :Credit Card Coded Data Good

Case		Status (MARITAL)	Sex	Age	Employment			Town	Nationality	Annual Income		BBK CUSTOMER	No. OF LOANS WITH BBK & OTHER F. INSTIT-UTIONS	No Of Credit Cards Held	Minimum Payment Rate	Credit Limit		Frequency Of Cash With-drawals	Frequency Of Late Payment	Excess Above Limit	No Of Payments In Arrears	Bounced Payments	Guarantee	Branch		Loan Officer	Length Of Longest Spell Of Arrears
		Married=1	Male=1					Nairobi=1	Kenyan=1			BBK Customer=1											With Guarantee=1			Vetting Manager=1	(DAYS)
		Single=0	Female=0					Others=0	Others=0			Other Banks=0											Without Guarantee=0			Acting V Manager=0	
Case	CLASS	MARITAL	Sex	Age	Empl	EmpCl	EmpClcD	Town	Nation	Ainco	AincoCl	BBKCus	NoCrH	NoLOAN	MPR	CrLIM	CrLIMCl	FoCW	FoLP	EAL	NoPiArr	BouPay	GUARA	Branch	BranchC	LOfficer	LoArreas
1	1	1	1	46	ABBEY INVESTMENTS LTD	Private		1	1	623000		0	1	1	0.2	2E+05		2	0	0	0	0	0	WESTLANDS		0	0
2	1	1	1	52	SHAH MUNGE & PARTNERS LTD	Private		1	1	480000		1	0	1	0.5	2E+05		1	0	0	0	0	0	QUEENSWAY		0	0
3	1	1	1	42	EAST AFRICAN CEMENT	Private		1	1	615000		0	0	1	0.1	96000		3	0	0	0	0	0	QUEENSWAY		1	0
4	1	1	1	59	NAIROBI CITY COUNCIL	Para		1	1	380000		1	0	1	0.1	66000		3	1	0	0	0	0	QUEENSWAY		0	0
5	1	1	1	54	GENERAL ACCIDENT INSURANCE CO.	Private		1	1	750000		1	2	1	0.2	1E+05		5	0	0	0	0	0	QUEENSWAY		1	2
6	1	1	1	47	MITSUBISHI CORPORATION	Private		1	1	727200		1	1	1	0.3	2E+05		0	0	0	0	0	0	QUEENSWAY		1	0
7	1	1	1	49	FIRESTONE [E.A] 1969 LTD	Private		0	1	480000		0	2	1	0.5	66000		0	0	0	0	0	0	NKRUMAH ROAD		0	0
8	1	1	1	35	FIRESTONE E.A (1969)LTD	Private		1	1	400000		0	2	1	0.1	50000		1	0	0	0	0	0	HURLINGHAM		0	0
9	1	1	1	45	GREENSTATES SCHOOL	Private		0	1	840000		1	1	2	0.1	66000		2	0	0	0	0	0	THIKA		1	8
10	1	1	1	42	KENYA POWER & LIGHTING CO.LTD	Para		1	1	648000		1	0	1	0.1	91000		2	0	0	0	0	0	WESTLANDS		1	1
11	1	1	1	48	COOPERS & LYBRAND	Private		1	1	996000		1	0	1	1	50000		2	0	0	0	0	0	QUEENSWAY		1	0
12	1	1	1	36	VICTORIA COMMERCIAL BANK	Bank		1	1	700200		1	0	1	0.8	1E+05		2	0	0	0	0	0	MARKET		1	0
13	1	1	1	42	CONSTRUCTION PROJECT CONSULTAN	Private		0	1	727560		0	0	1	0.3	50000		6	0	0	0	0	0	KITALE		1	0
14	1	1	1	45	KENYA POWER & LIGHTING CO.LTD	Private		1	1	840000		1	0	1	0.1	2E+05		3	0	0	0	0	1	ENTERPRISE RD		1	0
15	1	1	0	39	GLAXO WELLCOME (K) LTD	Private		1	1	[illegible]		0	2	1	0.1	50000		3	0	0	0	0	0	WESTLANDS		1	0
16	1	0	1	33	MICRO REGISTRARS LTD	Private		1	1	1E+06		1	0	1	0.1	75000		2	0	0	0	0	0	MARKET		1	0
17	1	1	0	40	SELF EMPLOYED (GR COLLECTIONS)	Self		1	1	690192		1	3	1	0.2	2E+05		2	0	0	0	0	1	QUEENSWAY		0	0
18	1	1	1	31	CUSSONS	Private		1	1	720000		0	1	1	0.1	1E+05		1	0	0	0	0	0	ENTERPRISE RD		1	0
19	1	0	0	28	AIRLINK LTD	Private		1	1	372000		1	0	1	0.1	76000		1	0	0	0	0	0	ENTERPRISE RD		1	0

Case		Status (MARITAL)	Sex	Age	Employment			Town	Nationality	Annual Income		BBK CUSTOMER	No. OF LOANS WITH BBK & OTHER F INSTIT-UTIONS	No Of Credit Cards Held	Minimum Payment Rate	Credit Limit		Frequency Of Cash With-drawals	Frequency Of Late Payment	Excess Above Limit	No Of Payments in Arrears	Bounced Payments	Guarantee	Branch		Loan Officer	Length Of Longest Spell Of Arrears
20	1	1	1	44	MIGITI ENTERPRISES LTD	Private		1	1	720000		1	0	1	0.1	92000		1	0	0	0	0	0	KAREN		1	0
21	1	1	0	32	I.C.A.O	Private		1	1	456000		1	0	2	0.5	1E+05		1	1	0.1	0	1	0	WESTLANDS		1	12
22	1	1	1	29	YAKO LTD	Private		0	1	96000		1	0	2	0.1	50000		1	0	0	0	0	0	NAKURU EAST		1	0
23	1	1	1	36	BAT (K) LTD	Private		1	1	589000		1	0	1	1.1	40000		0	0	0	0	0	0	HURLINGHAM		1	0
24	1	1	1	33	DEL MONTE KENYA LTD	Private		0	0	1E+06		0	0	1	0.5	2E+05		5	0	0	0	0	0	THIKA		1	0
25	1	1	1	42	BHOGAL'S GARAGE LTD	Private		0	1	3E+06		1	0	1	0.1	66000		1	0	0	0	0	0	MOI AVENUE		1	0
26	1	1	1	38	PFIZER LABS	Private		1	1	########		1	0	1	0.1	50000		1	0	0	0	0	0	MOI AVENUE		0	1
27	1	1	1	38	CARNAUDMETAL BOX K LTD	Private		1	1	1E+06		1	0	1	0.1	96000		2	0	0	0	0	0	MOI AVENUE		0	0
28	1	1	1	32	M PINNACLE ENG/HARD WARE	Private		1	1	1E+06		1	1	1	0.2	60000		4	0	0	0	0	0	MOI AVENUE		0	0
29	1	1	1	41	FINERALF FOREX BUREAU	Private		1	1	1E+06		0	0	1	0.1	2E+05		6	0	0	0	0	0	MOI AVENUE		0	0
30	1	1	1	46	BARKER & BARTON (K) LTD	Private		1	1	1E+06		1	2	1	0.3	86000		2	0	0	0	0	0	QUEENSWAY		1	0
31	1	1	1	37	DYER AND BLAIR LTD	Private		1	1	1E+06		1	2	1	0.1	81000		2	0	0	0	0	0	MARKET		0	0
32	1	1	1	39	LIVINGSTONE REGISTRARS LTD	Private		1	1	1E+06		1	1	1	0.1	66000		2	0	0	0	0	0	MARKET		0	0
33	1	1	1	41	AKIBA BANK LTD	Bank		1	1	1E+06		1	0	1	0.1	86000		2	0	0	0	1	0	MARKET		0	5
34	1	0	1	30	ABERCROMBIE & KENT (COAST) LTD	Private		0	1	330000		1	0	1	0.1	70000		2	0	0	0	0	0	DIGO ROAD		0	0
35	1	1	1	47	PRICEWATERHOUSE COPPERS	Private		0	1	1E+06		1	0	1	0.5	1E+05		1	0	0	0	0	0	HAILE SELASSIE		0	0
36	1	1	1	31	GLAXO WELLCOME (K) LTD	Private		1	1	387000		1	0	1	0.2	1E+05		0	0	0	0	0	0	AIRPORT		0	0
37	1	1	1	45	E A STORAGE CO LTD	Private		0	1	667200		1	0	1	0.2	1E+05		0	0	0	0	0	0	MARKET		0	0
38	1	1	1	33	ICL KENYA LTD	Private		0	1	720000		1	0	1	0.1	1E+05		0	0	0	0	0	0	MARKET		0	0
39	1	1	1	44	SELF EMPLOYED	Self		0	1	600000		1	1	1	0.1	82000		2	0	0	0	0	0	NKRUMAH ROAD		0	0
40	1	1	1	28	CHAVDA DITEN DINU	Private		0	1	240000		1	0	3	0.1	40000		2	3	0.1	0	1	0	KAKAMEGA		1	0
41	1	1	1	38	MOTOR MART LTD/YAMAHA MOTORS	Private		1	1	869316		1	0	1	0.1	66000		3	0	0	0	0	0	WESTLANDS		1	0
42	1	1	1	49	280 INVESTMENTS LTD	Private		1	1	600000		1	0	1	1	1E+05		5	0	0	0	0	0	ENTERPRISE RD		1	0
43	1	1	1	34	FREELANCE ACCOUNTANTS	Private		1	1	450000		0	1	1	0.1	80000		8	0	0	0	0	0	ENTERPRISE RD		0	0
44	1	1	1	37	MOTOR MART	Private		1	1	1E+06		0	1	1	0.1	86000		6	0	0	0	0	0	WESTLANDS		1	10

Case		Status (MARITAL)	Sex	Age	Employment			Town	Nationality	Annual Income		BBK CUSTOMER	No OF LOANS WITH BBK & OTHER F. INSTIT-UTIONS	No Of Credit Cards Held	Minimum Payment Rate	Credit Limit		Frequency Of Cash With-drawals	Frequency Of Late Payment	Excess Above Limit	No Of Payments In Arrears	Bounced Payments	Guarantee	Branch		Loan Officer	Length Of Longest Spell Of Arrears
45	1	1	0	35	GERMAN SCHOOL SOCIETY	Private		1	1	1E+06		1	1	2	0.2	66000		3	1	0	0	0	0	MOI AVENUE		1	0
46	1	1	1	37	CENTRAL BANK OF KENYA	Bank		1	1	2E+06		1	2	1	0.6	82000		3	0	0	0	0	0	MOI AVENUE		1	0
47	1	1	1	35	KAPLAN & STRATTON	Private		1	1	2E+06		1	0	1	0.3	45000		3	1	0	0	0	0	WESTLANDS		1	2
48	1	1	1	40	GENERAL MOTORS KENYA	Private		1	1	2E+06		1	0	1	0.3	91000		2	0	0	0	0	0	KAREN		1	0
49	1	1	1	36	ICRAF	Private		1	1	1E+06		1	1	1	0.2	43000		2	0	0	0	0	0	WESTLANDS		1	0
50	1	1	1	31	CO-OP BANK	Bank		1	1	900000		0	0	1	0.2	1E+05		2	0	0	0	0	0	QUEENSWAY		1	0
51	1	1	1	37	NAIROBI UNIVERSITY	Para		1	1	420000		1	0	1	0.2	70000		6	0	0	0	1	0	QUEENSWAY		1	0
52	1	1	1	48	MOBILE 072-746147	None		1	1	2E+06		1	2	1	0.2	86000		1	0	0	0	0	0	QUEENSWAY		1	0
53	1	1	1	43	TOP SPEED FREIGHT FORW LTD	Private		1	1	525720		1	1	1	0.1	1E+05		1	0	0	0	0	0	WESTLANDS		1	0
54	1	1	1	35	ARCHDIOCESE OF NAIROBI	Private		1	1	100000		0	1	1	0.1	66000		1	2	0	0	0	0	AIRPORT		1	0
55	1	1	1	36	UNGA GROUP LTD	Private		1	1	2E+06		1	0	1	0.1	45000		1	0	0	0	0	0	HAILE SELASSIE		1	0
56	1	1	1	39	SABIL KENYA	Private		0	1	720000		1	0	1	0.1	53000		0	0	0	0	0	0	QUEENSWAY		1	0
57	1	1	1	33	KENYA SHELL LTD	Private		1	1	930900		1	0	2	0.1	1E+05		3	0	0	0	0	0	AIRPORT		1	0
58	1	1	1	47	IPPF:AFRICA REGION	Private		1	1	2E+06		0	0	1	0.1	86000		3	0	0	0	0	0	AIRPORT		1	0
59	1	1	1	53	AFRICA ALLIANCE OF YMCA	Private		1	1	1E+06		0	0	1	0.1	1E+05		3	0	0	0	0	0	AIRPORT		0	0
60	1	1	1	42	HAMILTON HARRISON & MA	Private		1	1	960000		1	0	1	0.2	2E+05		2	0	0	0	0	0	MARKET		1	0
61	1	1	1	49	MUKIRI & COMPANY	Self		1	1	1E+06		1	0	1	1	3E+05		5	0	0	0	0	1	WESTLANDS		1	0
62	1	1	0	29	MANUFACTURING & CONSULTANCY	Private		1	1	600000		1	2	1	0.1	38000		1	0	0	0	0	0	MARKET		1	0
63	1	1	1	45	TSUBIS LTD	Private		1	1	3E+06		1	2	1	0.1	1E+05		1	0	0	0	0	0	MARKET		0	0
64	1	1	1	35	EXPORT PROMOTION COUNCIL	Para		1	1	789000		1	2	2	0.2	48000		0	0	0	0	0	0	RAHIMTULLA PRESTIGE		0	0
65	1	1	1	38	SEMBHI ENTERPRISES	Private		0	1	256000		1	1	1	0.5	50000		1	0	0	0	0	0	NYERI		1	0
66	1	1	1	34	TWIGA CHEMICAL IND. LTD	Private		1	1	758240		1	0	1	0.1	56000		1	0	0	0	0	0	PLAZA		1	0
67	1	1	0	30	ORGANISATION OF AFRICA UNITY	Inter		0	1	780000		1	0	1	0.1	1E+05		3	0	0	0	2	0	LAVINGTON		1	30
68	1	1	1	41	STANDARD CHARTERED BANK	Bank		1	1	2E+06		0	3	1	0.8	1E+05		1	0	0	0	0	0	HURLINGHAM		1	0
69	1	1	1	36	MOSAL CLEANING ENTERPRISE	Private		0	1	4E+06		1	0	4	0.5	66000		1	0	0	0	0	0	MERU		1	0

Case		Status (MARITAL)	Sex	Age	Employment			Town	Nationality	Annual Income		BBK CUSTOMER	No OF LOANS WITH BBK & OTHER F. INSTIT-UTIONS	No Of Credit Cards Held	Minimum Payment Rate	Credit Limit		Frequency Of Cash With-drawals	Frequency Of Late Payment	Excess Above Limit	No Of Payments In Arrears	Bounced Payments	Guarantee	Branch		Loan Officer	Length Of Longest Spell Of Arrears
70	1	1	0	30	CPC (K) LTD	Private		1	1	700000		1	0	1	0.1	66000		4	0	0	0	0	0	QUEENSWAY		1	0
71	1	1	1	37	NAIROBI CITY COUNCIL	Para		1	1	491400		1	0	1	0.1	86000		4	1	0	0	0	0	QUEENSWAY		0	0
72	1	1	1	33	KENYA BREWERIES	Private		1	1	1E+06		1	1	1	0.1	30000		6	0	0	0	0	0	QUEENSWAY		1	0
73	1	0	0	28	TSC	Gov		1	1	600000		1	0	1	0.1	76000		8	0	0	0	0	0	QUEENSWAY		1	0
74	1	1	1	35	KENYA BREWERIES LTD	Private		1	1	1E+06		0	0	1	0.4	86000		2	0	0	0	0	0	MARKET		1	0
75	1	1	1	33	KAGIO ESSO SERVICE STATION	Private		0	1	720000		1	0	1	0.1	40000		2	0	0	0	0	0	HAILE SELASSIE		1	0
76	1	1	1	40	DATOO ASS	Private		0	1	2E+06		0	0	3	0.1	50000		1	0	0	0	0	0	WESTLANDS		1	0
77	1	1	1	38	WORLD BANK/NARP	Inter		1	1	4E+06		1	3	3	0.2	1E+05		1	0	0	0	0	0	ENTERPRISE RD		1	0
78	1	1	1	36	GEMINI STORES	Private		1	1	1E+06		1	1	4	0.5	1E+05		1	0	0.1	0	1	0	ENTERPRISE RD		1	3
79	1	1	1	37	EATEC LTD	Private		1	1	2E+06		1	0	1	0.2	96000		1	1	0	0	0	0	ENTERPRISE RD		0	0
80	1	1	1	41	KENYA PIPELINE CO. LTD	Para		0	1	1E+06		1	0	1	0.1	50000		0	0	0	0	0	0	WUNDANYI		1	0
81	1	1	1	33	HERITAGE INSURANCE CO	Private		1	1	691932		1	0	1	0.1	40000		0	0	0	0	0	0	RUARAKA		1	0
82	1	1	0	31	TAR UNIVERSITY	Private		1	1	375240		1	0	1	0.1	60000		3	0	0	0	0	0	RUARAKA		1	0
83	1	1	1	45	UNITED TOURING CO. LTD	Private		0	1	648000		1	2	1	0.1	53000		2	0	0	0	0	0	MALINDI		0	0
84	1	1	1	41	KENYA BREWERIES LTD	Private		1	1	486120		0	0	1	0.1	50000		2	2	0	0	0	0	RUARAKA		0	0
85	1	1	1	33	KCB LTD	Bank		1	1	720000		0	2	1	0.6	1E+05		0	0	0	0	0	0	MUTHAIGA		0	0
86	1	1	0	33	COCA-COLA AFRICA LTD	Private		1	1	844800		1	2	1	0.1	66000		1	0	0	0	0	0	MUTHAIGA		1	0
87	1	1	1	36	FIRST ASSURANCE CO.LTD	Private		0	1	4E+06		1	2	1	0.5	1E+05		3	0	0	0	0	0	NKRUMAH ROAD		1	20
88	1	1	0	34	BARCLAYS BANK	Bank		1	1	1E+06		0	1	2	0.6	96000		3	0	0	0	0	0	RUARAKA		1	0
89	1	1	1	32	AON MINET INS BROKERS LTD	Private		1	1	1E+06		0	0	1	0.8	1E+05		3	0	0	0	0	0	HAILE SELASSIE		1	0
90	1	1	1	36	C M C	Private		1	1	1E+06		0	0	1	1	2E+05		3	0	0	0	0	1	ENTERPRISE RD		1	0
91	1	1	1	36	E A.DEVELOPMENT BANK	Bank		1	1	806192		1	0	1	0.3	82000		3	0	0	0	0	0	ENTERPRISE RD		1	0
92	1	1	1	45	PANESAR ENGINEERING ENT.	Private		0	1	1E+06		1	0	1	0.1	66000		3	1	0	0	0	0	ELDORET		1	0
93	1	1	1	37	KIRUI CONSULTANTS	Private		1	1	750000		1	0	1	0.1	1E+05		2	0	0	0	0	0	QUEENSWAY		1	0
94	1	1	1	48	PEMBE FLOUR MILLS	Private		1	1	2E+06		1	2	2	0.1	66000		5	0	0	0	0	0	KAREN		1	0

Case		Status (MARITAL)	Sex	Age	Employment			Town	Nationality	Annual Income		BBK CUSTOMER	No. OF LOANS WITH BBK & OTHER F. INSTIT-UTIONS	No Of Credit Cards Held	Minimum Payment Rate	Credit Limit		Frequency Of Cash With-drawals	Frequency Of Late Payment	Excess Above Limit	No Of Payments In Arrears	Bounced Payments	Guarantee	Branch		Loan Officer	Length Of Longest Spell Of Arrears
95	1	1	0	41	UNICEF	Inter		1	1	2E+06		1	0	2	0.8	66000		0	0	0	0	0	0	MUTHAIGA		1	0
96	1	1	1	32	MISS COMM OF ST PAUL	Inter		1	1	750000		1	0	1	0.1	66000		3	0	0	0	0	0	MUTHAIGA		1	0
97	1	1	1	38	JUDICIARY	Gov		0	1	563000		1	0	1	0.1	68000		2	0	0	0	0	0	NANYUKI		1	0
98	1	1	1	31	CITY X-RAY SERVICES	Private		1	1	812000		1	0	1	0.1	66000		2	0	0	0	0	0	QUEENSWAY		1	2
99	1	1	1	32	AMEDO	Private		1	1	1E+06		0	1	1	0.2	80000		2	0	0	0	0	0	JKIA		1	0
100	1	1	1	33	AMEDO CENTRE (K) LTD	Private		1	1	1E+06		1	0	1	0.1	1E+05		1	0	0	0	0	0	KAREN		1	0
																										1	

Appendix 5 :Covariances

Pooled Within-Groups Matrices

Covariance

	MARITAL	SEX	AGE	EMPCLCD	TOWN	NATION	AINCOCL	BBKCUS	NOCRH	NOLOAN	MPR	CRLIMCL	FOCW	FOLP	EAL	NOPIARR	BOUPAY	GUARA	BRANCHC	LOARREAS	LOARREAC
MARITAL	0.128	0.015	1.014	0.024	-0.009	-0.002	0.004	0.016	-0.002	0.014	0.006	0.020	-0.120	0.016	-0.007	-0.032	-0.026	0.004	0.025	-1.511	-0.031
SEX	0.015	0.095	0.506	0.014	-0.019	-0.001	0.006	-0.001	-0.001	-0.004	-0.002	0.026	-0.043	-0.041	-0.002	-0.007	-0.012	-0.002	0.146	-0.505	-0.032
AGE	1.014	0.506	37.327	-0.260	-0.365	-0.002	0.127	0.130	0.156	-0.369	0.256	0.613	-0.710	0.673	-0.086	-0.523	-0.114	0.062	-0.557	-16.665	-0.494
EMPCLCD	0.024	0.014	-0.260	4.699	0.090	-0.009	0.157	0.088	0.167	0.150	0.047	0.312	0.830	0.351	0.041	0.142	0.320	0.013	0.269	8.775	0.249
TOWN	-0.009	-0.019	-0.365	0.090	0.177	0.003	0.027	-0.024	0.022	-0.014	0.006	0.102	0.163	-0.017	0.004	0.032	0.016	0.007	-0.809	2.221	0.049
NATION	-0.002	-0.001	-0.002	-0.009	0.003	0.010	-0.009	0.001	0.002	0.006	-0.003	-0.005	-0.012	0.016	0.000	0.004	0.001	0.000	-0.009	0.113	0.004
AINCOCL	0.004	0.006	0.127	0.157	0.027	-0.009	1.004	0.012	-0.002	0.045	0.004	0.183	0.045	-0.071	0.003	-0.027	0.005	0.018	-0.640	0.571	0.039
BBKCUS	0.016	-0.001	0.130	0.088	-0.024	0.001	0.012	0.209	-0.030	0.049	-0.025	-0.020	-0.064	-0.042	0.000	0.011	-0.025	0.001	0.002	-0.037	-0.008
NOCRH	-0.002	-0.001	0.156	0.167	0.022	0.002	-0.002	-0.030	0.784	0.027	-0.006	0.086	0.264	-0.004	0.018	0.058	0.126	-0.006	-0.798	-0.229	0.002
NOLOAN	0.014	-0.004	-0.369	0.150	-0.014	0.006	0.045	0.049	0.027	0.818	-0.034	0.069	0.517	-0.075	0.040	0.050	0.071	0.001	0.491	0.981	-0.017
MPR	0.006	-0.002	0.256	0.047	0.006	-0.003	0.004	-0.025	-0.006	-0.034	0.082	0.040	0.009	0.050	0.001	-0.021	0.054	0.003	-0.067	0.069	0.010
CRLIMCL	0.020	0.026	0.613	0.312	0.102	-0.005	0.183	-0.020	0.086	0.069	0.040	1.500	0.241	0.058	0.004	-0.020	0.074	0.043	-1.273	1.576	0.111
FOCW	-0.120	-0.043	-0.710	0.830	0.163	-0.012	0.045	-0.064	0.264	0.517	0.009	0.241	7.425	0.643	0.278	1.438	1.179	0.021	-2.379	41.104	1.042
FOLP	0.016	-0.041	0.673	0.351	-0.017	0.016	-0.071	-0.042	-0.004	-0.075	0.050	0.058	0.643	2.893	0.037	0.032	0.465	-0.013	-0.070	2.193	0.076
EAL	-0.007	-0.002	-0.086	0.041	0.004	0.000	0.003	0.000	0.018	0.040	0.001	0.004	0.278	0.037	0.023	0.095	0.079	0.000	-0.019	2.621	0.066
NOPIARR	-0.032	-0.007	-0.523	0.142	0.032	0.004	-0.027	0.011	0.058	0.050	-0.021	-0.020	1.438	0.032	0.095	1.726	0.724	-0.014	-1.228	45.904	1.171
BOUPAY	-0.026	-0.012	-0.114	0.320	0.016	0.001	0.005	-0.025	0.126	0.071	0.054	0.074	1.179	0.465	0.079	0.724	1.051	-0.019	-0.392	22.138	0.611
GUARA	0.004	-0.002	0.062	0.013	0.007	0.000	0.018	0.001	-0.006	0.001	0.003	0.043	0.021	-0.013	0.000	-0.014	-0.019	0.029	-0.047	-0.388	-0.016
BRANCHC	0.025	0.146	-0.557	0.269	-0.809	-0.009	-0.640	0.002	-0.798	0.491	-0.067	-1.273	-2.379	-0.070	-0.019	-1.228	-0.392	-0.047	66.906	-29.651	-0.890
LOARREAS	-1.511	-0.505	-16.665	8.775	2.221	0.113	0.571	-0.037	-0.229	0.981	0.069	1.576	41.104	2.193	2.621	45.904	22.138	-0.388	-29.651	1552.615	41.572
LOARREAC	-0.031	-0.032	-0.494	0.249	0.049	0.004	0.039	-0.008	0.002	-0.017	0.010	0.111	1.042	0.076	0.066	1.171	0.611	-0.016	-0.890	41.572	1.447

Correlation

	MARITAL	SEX	AGE	EMPCLCD	TOWN	NATION	AINCOCL	BBKCUS	NOCRH	NOLOAN	MPR	CRLIMCL	FOCW	FOLP	EAL	NOPIARR	BOUPAY	GUARA	BRANCHC	LOARREAS	LOARREAC
MARITAL	1.000	0.138	0.464	0.031	-0.059	-0.050	0.010	0.099	-0.008	0.042	0.063	0.046	-0.123	0.027	-0.127	-0.068	-0.072	0.065	0.009	-0.107	-0.071
SEX	0.138	1.000	0.269	0.022	-0.148	-0.035	0.019	-0.010	-0.004	-0.015	-0.024	0.068	-0.051	-0.078	-0.033	-0.017	-0.039	-0.030	0.058	-0.042	-0.086
AGE	0.464	0.269	1.000	-0.020	-0.142	-0.003	0.021	0.046	0.029	-0.067	0.146	0.082	-0.043	0.065	-0.093	-0.065	-0.018	0.059	-0.011	-0.069	-0.067
EMPCLCD	0.031	0.022	-0.020	1.000	0.098	-0.042	0.072	0.088	0.087	0.077	0.076	0.117	0.141	0.095	0.123	0.050	0.144	0.034	0.015	0.103	0.095
TOWN	-0.059	-0.148	-0.142	0.098	1.000	0.066	0.065	-0.123	0.058	-0.036	0.053	0.199	0.142	-0.023	0.062	0.058	0.038	0.096	-0.235	0.134	0.098
NATION	-0.050	-0.035	-0.003	-0.042	0.066	1.000	-0.092	0.013	0.028	0.064	-0.101	-0.039	-0.043	0.094	0.016	0.032	0.014	0.018	-0.011	0.029	0.033
AINCOCL	0.010	0.019	0.021	0.072	0.065	-0.092	1.000	0.027	-0.002	0.050	0.015	0.149	0.016	-0.041	0.020	-0.020	0.005	0.105	-0.078	0.014	0.032
BBKCUS	0.099	-0.010	0.046	0.088	-0.123	0.013	0.027	1.000	-0.074	0.118	-0.195	-0.036	-0.052	-0.054	-0.004	0.018	-0.053	0.016	0.001	-0.002	-0.015
NOCRH	-0.008	-0.004	0.029	0.087	0.058	0.028	-0.002	-0.074	1.000	0.033	-0.022	0.079	0.110	-0.003	0.136	0.050	0.139	-0.038	-0.110	-0.007	0.002
NOLOAN	0.042	-0.015	-0.067	0.077	-0.036	0.064	0.050	0.118	0.033	1.000	-0.133	0.063	0.210	-0.049	0.293	0.042	0.077	0.010	0.066	0.028	-0.016
MPR	0.063	-0.024	0.146	0.076	0.053	-0.101	0.015	-0.195	-0.022	-0.133	1.000	0.113	0.011	0.103	0.023	-0.056	0.185	0.064	-0.029	0.006	0.028
CRLIMCL	0.046	0.068	0.082	0.117	0.199	-0.039	0.149	-0.036	0.079	0.063	0.113	1.000	0.072	0.028	0.022	-0.012	0.059	0.204	-0.127	0.033	0.075
FOCW	-0.123	-0.051	-0.043	0.141	0.142	-0.043	0.016	-0.052	0.110	0.210	0.011	0.072	1.000	0.139	0.675	0.402	0.422	0.045	-0.107	0.383	0.318
FOLP	0.027	-0.078	0.065	0.095	-0.023	0.094	-0.041	-0.054	-0.003	-0.049	0.103	0.028	0.139	1.000	0.144	0.014	0.267	-0.045	-0.005	0.033	0.037
EAL	-0.127	-0.033	-0.093	0.123	0.062	0.016	0.020	-0.004	0.136	0.293	0.023	0.022	0.675	0.144	1.000	0.479	0.512	0.017	-0.016	0.439	0.362
NOPIARR	-0.068	-0.017	-0.065	0.050	0.058	0.032	-0.020	0.018	0.050	0.042	-0.056	-0.012	0.402	0.014	0.479	1.000	0.537	-0.060	-0.114	0.887	0.741
BOUPAY	-0.072	-0.039	-0.018	0.144	0.038	0.014	0.005	-0.053	0.139	0.077	0.185	0.059	0.422	0.267	0.512	0.537	1.000	-0.107	-0.047	0.548	0.495
GUARA	0.065	-0.030	0.059	0.034	0.096	0.018	0.105	0.016	-0.038	0.010	0.064	0.204	0.045	-0.045	0.017	-0.060	-0.107	1.000	-0.033	-0.057	-0.078
BRANCHC	0.009	0.058	-0.011	0.015	-0.235	-0.011	-0.078	0.001	-0.110	0.066	-0.029	-0.127	-0.107	-0.005	-0.016	-0.114	-0.047	-0.033	1.000	-0.092	-0.090
LOARREAS	-0.107	-0.042	-0.069	0.103	0.134	0.029	0.014	-0.002	-0.007	0.028	0.006	0.033	0.383	0.033	0.439	0.887	0.548	-0.057	-0.092	1.000	0.877
LOARREAC	-0.071	-0.086	-0.067	0.095	0.098	0.033	0.032	-0.015	0.002	-0.016	0.028	0.075	0.318	0.037	0.362	0.741	0.495	-0.078	-0.090	0.877	1.000

a The covariance matrix has 197 degrees of freedom.

Appendix 6 :Descriptive Statistics

Descriptive Statistics: MARITAL, Sex, Age, EmpClcD, Town, Nation, Ainco, AincoCl

Variable	N	N*	Mean	Median	TrMean	StDev
MARITAL	200	0	0.8250	1.0000	0.8611	0.3809
Sex	200	0	0.8950	1.0000	0.9389	0.3073
Age	200	0	37.385	36.000	37.039	6.195
EmpClcD	199	1	2.608	1.000	2.397	2.238
Town	200	0	0.7750	1.0000	0.8056	0.4186
Nation	200	0	0.99000	1.00000	1.00000	0.09975
Ainco	200	0	1087458	865658	993715	771227
AincoCl	200	0	2.5950	3.0000	2.6056	1.0030
BBKCus	200	0	0.5600	1.0000	0.5667	0.4976
NoCrH	200	0	1.2500	1.0000	1.1889	1.1062
NoLOAN	200	0	1.5700	1.0000	1.4944	0.9694
MPR	200	0	0.3657	0.2000	0.3447	0.3050
CrLIM	200	0	83175	70000	78778	42026
CrLIMCl	200	0	2.5350	2.0000	2.5389	1.2314
FoCW	200	0	3.830	3.000	3.544	3.151
FoLP	200	0	3.080	3.000	2.844	3.399
EAL	200	0	0.2646	0.1600	0.2399	0.3023
NoPiArr	200	0	2.415	1.000	2.211	2.751
BouPay	200	0	2.140	2.000	1.983	2.312
GUARA	200	0	0.0300	0.0000	0.0000	0.1710
BranchC	200	0	12.080	9.000	11.461	8.246
Lofficer	200	0	0.5350	1.0000	0.5389	0.5000
LoArreas	200	0	71.10	27.00	64.83	80.51
LoArreaC	200	0	4.895	5.000	4.772	3.817

Variable	SE Mean	Minimum	Maximum	Q1	Q3
MARITAL	0.0269	0.0000	1.0000	1.0000	1.0000
Sex	0.0217	0.0000	1.0000	1.0000	1.0000
Age	0.438	28.000	59.000	33.000	41.000
EmpClcD	0.159	1.000	8.000	1.000	4.000
Town	0.0296	0.0000	1.0000	1.0000	1.0000
Nation	0.00705	0.00000	1.00000	1.00000	1.00000
Ainco	54534	96000	4680000	603740	1285275
AincoCl	0.0709	1.0000	4.0000	2.0000	3.0000
BBKCus	0.0352	0.0000	1.0000	0.0000	1.0000
NoCrH	0.0782	0.0000	4.0000	0.0000	2.0000
NoLOAN	0.0685	0.0000	6.0000	1.0000	2.0000
MPR	0.0216	0.1000	1.1000	0.1000	0.6000
CrLIM	2972	25000	300000	50000	100000
CrLIMCl	0.0871	1.0000	4.0000	1.0000	4.0000
FoCW	0.223	0.000	16.000	2.000	5.000
FoLP	0.240	0.000	12.000	0.000	6.000
EAL	0.0214	0.0000	1.2500	0.0000	0.4800

Appendix 7 :Correlations

Results for: Data For Final Analysis

	MARITAL	Sex	Age	EmpClcD	Town	Nation	AincoCl	BBKCus
Sex	0.100							
	0.160							
Age	0.482	0.254						
	0.000	0.000						
EmpClcD	-0.063	0.042	-0.058					
	0.374	0.553	0.420					
Town	-0.059	-0.145	-0.137	0.099				
	0.406	0.040	0.053	0.165				

	MARITAL	Sex	Age	EmpClcD	Town	Nation	AIncoCl	BBKCus
Nation	-0.046	-0.034	-0.002	-0.040	0.066			
	0.515	0.628	0.979	0.572	0.352			
AIncoCl	-0.002	0.024	0.026	0.081	0.069	-0.091		
	0.974	0.732	0.714	0.256	0.331	0.200		
BBKCus	0.228	-0.041	0.109	-0.025	-0.116	0.012	0.014	
	0.001	0.567	0.124	0.727	0.103	0.864	0.847	
NoCrH	-0.218	0.048	-0.062	0.223	0.057	0.023	0.028	-0.292
	0.002	0.499	0.385	0.002	0.423	0.749	0.691	0.000
NoLOAN	-0.096	0.016	-0.121	0.164	-0.029	0.059	0.058	-0.050
	0.177	0.818	0.087	0.020	0.683	0.405	0.417	0.478
MPR	-0.073	0.007	0.076	0.161	0.053	-0.094	0.025	-0.312
	0.301	0.922	0.287	0.023	0.452	0.186	0.725	0.000
CrLIMCl	0.093	0.056	0.104	0.076	0.196	-0.038	0.144	0.025
	0.188	0.429	0.143	0.286	0.005	0.593	0.042	0.723
FoCW	-0.280	-0.003	-0.119	0.248	0.127	-0.037	0.029	-0.247
	0.000	0.967	0.092	0.000	0.073	0.599	0.684	0.000
FoLP	-0.296	0.032	-0.106	0.269	-0.001	0.047	0.010	-0.374
	0.000	0.651	0.137	0.000	0.984	0.510	0.893	0.000
EAL	-0.367	0.054	-0.182	0.283	0.041	0.008	0.040	-0.351
	0.000	0.446	0.010	0.000	0.562	0.908	0.571	0.000
NoPIArr -	0.343	0.064	-0.169	0.249	0.038	0.015	0.021	-0.347
	0.000	0.370	0.017	0.000	0.595	0.831	0.766	0.000
BouPay	-0.349	0.056	-0.150	0.292	0.028	0.006	0.033	-0.383
	0.000	0.430	0.034	0.000	0.699	0.932	0.640	0.000
GUARA	0.081	-0.035	0.065	0.018	0.095	0.018	0.100	0.038
	0.254	0.619	0.361	0.803	0.182	0.804	0.157	0.595
BranchC	0.059	0.043	0.004	-0.024	-0.236	-0.011	-0.089	0.056
	0.408	0.546	0.954	0.736	0.001	0.874	0.210	0.428
Lofficer	0.098	-0.058	-0.107	-0.106	0.050	0.007	0.073	0.143
	0.166	0.417	0.130	0.137	0.484	0.921	0.301	0.043
LoArreaC	-0.358	0.051	-0.171	0.273	0.042	0.010	0.043	-0.387
	0.000	0.477	0.015	0.000	0.557	0.883	0.549	0.000

	NoCrH	NoLOAN	MPR	CrLIMCl	FoCW	FoLP	EAL	NoPlArr
NoLOAN	0.246							
	0.000							
MPR	0.198	0.020						
	0.005	0.783						
CrLIMCl	-0.021	0.004	0.053					
	0.766	0.952	0.456					
FoCW	0.377	0.358	0.193	-0.011				
	0.000	0.000	0.006	0.873				
FoLP	0.517	0.300	0.361	-0.110	0.501			
	0.000	0.000	0.000	0.121	0.000			
EAL	0.572	0.458	0.324	-0.112	0.731	0.788		
	0.000	0.000	0.000	0.113	0.000	0.000		
NoPlArr	0.545	0.346	0.293	-0.131	0.612	0.766	0.876	
	0.000	0.000	0.000	0.064	0.000	0.000	0.000	
BouPay	0.585	0.365	0.400	-0.102	0.617	0.837	0.891	0.902
	0.000	0.000	0.000	0.149	0.000	0.000	0.000	0.000
GUARA	-0.066	-0.013	0.039	0.210	0.010	-0.073	-0.043	-0.080
	0.350	0.858	0.583	0.003	0.894	0.302	0.550	0.260
BranchC	-0.180	0.008	-0.078	-0.105	-0.162	-0.128	-0.133	-0.181
	0.011	0.909	0.275	0.140	0.022	0.072	0.060	0.010
LOfficer	-0.279	-0.083	-0.113	-0.018	-0.149	-0.374	-0.365	-0.323
	0.000	0.244	0.110	0.797	0.035	0.000	0.000	0.000
LoArreaC	0.568	0.349	0.351	-0.112	0.569	0.829	0.880	0.946
	0.000	0.000	0.000	0.114	0.000	0.000	0.000	0.000

	BouPay	GUARA	BranchC	LOfficer
GUARA	-0.100			
	0.160			
BranchC	-0.150	-0.023		
	0.034	0.746		
LOfficer	-0.356	-0.012	0.013	
	0.000	0.862	0.858	
LoArreaC	0.921	-0.080	-0.165	-0.336
	0.000	0.261	0.020	0.000
Cell Contents: Pearson correlation				
P-Value				

Appendix 8: Case wise Statistics Summary Table

		Highest Group					Second Highest Group			
	Actual Group	Predicted Group	P(D>d | G=g)		P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Discriminant Scores Function 1
Case Number			p	df						
1	0	0	0.023	1	1	5.180	1	0.0000	29.314	1.550
2	0	0	0.921	1	1	0.010	1	0.0000	57.619	3.726
3	0	0	0.580	1	1	0.306	1	0.0000	67.951	4.379
4	0	0	0.999	1	1	0.000	1	0.0000	59.115	3.824
5	0	0	0.926	1	1	0.009	1	0.0000	57.724	3.733
6	0	0	0.252	1	1	1.315	1	0.0000	42.818	2.679
7	0	0	0.120	1	1	2.416	1	0.0000	37.648	2.271
8	0	0	0.330	1	1	0.949	1	0.0000	45.101	2.851
9	0	0	0.540	1	1	0.376	1	0.0000	68.950	4.439
10	0	0	0.718	1	1	0.130	1	0.0000	53.714	3.465
11	0	0	0.940	1	1	0.006	1	0.0000	57.986	3.750
12	0	0	0.242	1	1	1.371	1	0.0000	42.502	2.655
13	0	0	0.491	1	1	0.474	1	0.0000	49.019	3.137
14	0	0	0.641	1	1	0.217	1	0.0000	66.524	4.292
15	0	0	0.979	1	1	0.001	1	0.0000	58.726	3.799
16	0	0	0.950	1	1	0.004	1	0.0000	58.168	3.762
17	0	0	0.717	1	1	0.131	1	0.0000	64.838	4.188
18	0	0	0.012	1	1	6.320	1	0.0000	26.793	1.312
19	0	0	0.081	1	1	3.051	1	0.0000	89.053	5.572

		Highest Group					Second Highest Group			
	Actual Group	Predicted Group	P(D>d | G=g)		P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Discriminant Scores Function 1
Case Number			p	df						
20	0	0	0.199	1	1	1.647	1	0.0000	80.524	5.109
21	0	0	0.401	1	1	0.706	1	0.0000	72.770	4.666
22	0	0	0.011	1	1	6.463	1	0.0000	104.701	6.368
23	0	0	0.183	1	1	1.775	1	0.0000	81.406	5.158
24	0	0	0.786	1	1	0.074	1	0.0000	55.030	3.554
25	0	0	0.006	1	1	7.657	1	0.0003	24.235	1.059
26	0	0	0.322	1	1	0.980	1	0.0000	75.339	4.815
27	0	0	0.222	1	1	1.489	1	0.0000	41.859	2.605
28	0	0	0.287	1	1	1.133	1	0.0000	43.902	2.761
29	0	0	0.437	1	1	0.605	1	0.0000	47.779	3.048
30	0	0	0.373	1	1	0.793	1	0.0000	46.236	2.935
31	0	0	0.395	1	1	0.723	1	0.0000	46.785	2.976
32	0	0	0.414	1	1	0.668	1	0.0000	72.371	4.643
33	0	0	0.359	1	1	0.842	1	0.0000	74.097	4.744
34	0	0	0.023	1	1	5.144	1	0.0000	99.162	6.094
35	0	0	0.658	1	1	0.196	1	0.0000	66.149	4.269
36	0	0	0.222	1	1	1.489	1	0.0000	79.393	5.046
37	0	0	0.043	1	1	4.093	1	0.0000	94.345	5.849
38	0	0	0.791	1	1	0.070	1	0.0000	63.288	4.091
39	0	0	0.519	1	1	0.416	1	0.0000	69.476	4.471
40	0	0	0.091	1	1	2.861	1	0.0000	88.014	5.517
41	0	0	0.589	1	1	0.291	1	0.0000	67.730	4.365
42	0	0	0.741	1	1	0.109	1	0.0000	54.159	3.495
43	0	0	0.001	1	1	10.129	1	0.0000	118.215	7.008
44	0	0	0.564	1	1	0.332	1	0.0000	68.333	4.402
45	0	0	0.326	1	1	0.967	1	0.0000	44.983	2.843
46	0	0	0.399	1	1	0.710	1	0.0000	46.887	2.983
47	0	0	0.945	1	1	0.005	1	0.0000	60.199	3.894
48	0	0	0.958	1	1	0.003	1	0.0000	59.944	3.878
49	0	0	0.189	1	1	1.723	1	0.0000	40.673	2.513
50	0	0	0.790	1	1	0.071	1	0.0000	55.114	3.559
51	0	0	0.736	1	1	0.113	1	0.0000	64.427	4.162
52	0	0	0.135	1	1	2.230	1	0.0000	38.399	2.332
53	0	0	0.472	1	1	0.518	1	0.0000	48.586	3.106
54	0	0	0.752	1	1	0.100	1	0.0000	54.378	3.510
55	0	0	0.718	1	1	0.130	1	0.0000	53.721	3.465
56	0	0	0.106	1	1	2.607	1	0.0000	86.578	5.440
57	0	0	0.793	1	1	0.069	1	0.0000	55.175	3.564
58	0	0	0.271	1	1	1.213	1	0.0000	77.292	4.927
59	0	0	0.957	1	1	0.003	1	0.0000	59.969	3.880
60	0	0	0.755	1	1	0.097	1	0.0000	64.027	4.137
61	0	0	0.024	1	1	5.094	1	0.0000	98.943	6.083
62	0	0	0.832	1	1	0.045	1	0.0000	55.916	3.613

			Highest Group				Second Highest Group			
	Actual	Predicted	P(D>d | G=g)		P(G=g | D=d)	Squared	Group	P(G=g | D=d)	Squared	
	Group	Group				Mahalanobis			Mahalanobis	Discriminant
						Distance to			Distance to	Scores
						Centroid			Centroid	Function 1
Case Number			p	df						
63	0	0	0.866	1	1	0.029	1	0.0000	56.568	3.657
64	0	0	0.689	1	1	0.161	1	0.0000	65.461	4.226
65	0	0	0.204	1	1	1.617	1	0.0000	41.197	2.554
66	0	0	0.283	1	1	1.154	1	0.0000	43.768	2.751
67	0	0	0.198	1	1	1.655	1	0.0000	41.009	2.539
68	0	0	0.990	1	1	0.000	1	0.0000	58.954	3.814
69	0	0	0.745	1	1	0.106	1	0.0000	54.243	3.501
70	0	0	0.204	1	1	1.614	1	0.0000	80.289	5.096
71	0	0	0.077	1	1	3.128	1	0.0000	35.063	2.057
72	0	0	0.776	1	1	0.081	1	0.0000	54.850	3.542
73	0	0	0.244	1	1	1.355	1	0.0000	42.589	2.662
74	0	0	0.156	1	1	2.016	1	0.0000	82.994	5.246
75	0	0	0.045	1	1	4.032	1	0.0000	94.051	5.834
76	0	0	0.474	1	1	0.512	1	0.0000	70.650	4.541
77	0	0	0.124	1	1	2.364	1	0.0000	37.855	2.288
78	0	0	0.317	1	1	1.002	1	0.0000	44.741	2.824
79	0	0	0.719	1	1	0.130	1	0.0000	53.729	3.466
80	0	0	0.318	1	1	0.999	1	0.0000	44.766	2.826
81	0	0	0.214	1	1	1.541	1	0.0000	79.770	5.067
82	0	0	0.402	1	1	0.703	1	0.0000	46.947	2.987
83	0	0	0.677	1	1	0.173	1	0.0000	52.905	3.409
84	0	0	0.559	1	1	0.341	1	0.0000	68.457	4.410
85	0	0	0.159	1	1	1.988	1	0.0000	39.440	2.416
86	0	0	0.718	1	1	0.130	1	0.0000	64.817	4.187
87	0	0	0.126	1	1	2.336	1	0.0000	37.966	2.297
88	0	0	0.319	1	1	0.995	1	0.0000	44.793	2.828
89	0	0	0.419	1	1	0.653	1	0.0000	72.221	4.634
90	0	0	0.213	1	1	1.552	1	0.0000	79.852	5.072
91	0	0	0.989	1	1	0.000	1	0.0000	58.930	3.812
92	0	0	0.427	1	1	0.631	1	0.0000	47.550	3.031
93	0	0	0.421	1	1	0.649	1	0.0000	47.397	3.020
94	0	0	0.188	1	1	1.732	1	0.0000	81.113	5.142
95	0	0	0.025	1	1	5.024	1	0.0000	98.636	6.067
96	0	0	0.514	1	1	0.425	1	0.0000	49.533	3.174
97	0	0	0.619	1	1	0.247	1	0.0000	67.023	4.322
98	0	0	0.690	1	1	0.160	1	0.0000	65.440	4.225
99	0	0	0.033	1	1	4.540	1	0.0000	30.907	1.695
100	0	0	0.229	1	1	1.446	1	0.0000	79.076	5.028
101	1	1	0.812	1	1	0.056	0	0.0000	62.849	-4.102
102	1	1	0.812	1	1	0.057	0	0.0000	62.858	-4.103
103	1	1	0.510	1	1	0.434	0	0.0000	69.708	-4.523
104	1	1	0.911	1	1	0.012	0	0.0000	60.868	-3.976
105	1	1	0.215	1	1	1.536	0	0.0000	41.614	-2.625

	Actual Group	Predicted Group	Highest Group P(D>d | G=g) p	df	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Second Highest Group: Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Discriminant Scores Function 1
Case Number										
106	1	1	0.935	1	1	0.007	0	0.0000	57.881	-3.782
107	1	1	0.572	1	1	0.319	0	0.0000	50.765	-3.299
108	1	1	0.702	1	1	0.146	0	0.0000	53.409	-3.482
109	1	1	0.084	1	1	2.976	0	0.0000	35.580	-2.139
110	1	1	0.739	1	1	0.111	0	0.0000	54.127	-3.531
111	1	1	0.990	1	1	0.000	0	0.0000	59.328	-3.877
112	1	1	0.523	1	1	0.408	0	0.0000	69.364	-4.503
113	1	1	0.425	1	1	0.635	0	0.0000	72.031	-4.661
114	1	1	0.510	1	1	0.433	0	0.0000	69.695	-4.523
115	1	1	0.909	1	1	0.013	0	0.0000	57.390	-3.750
116	1	1	0.801	1	1	0.064	0	0.0000	63.079	-4.116
117	1	1	0.887	1	1	0.020	0	0.0000	56.963	-3.722
118	1	1	0.827	1	1	0.048	0	0.0000	62.557	-4.084
119	1	1	0.884	1	1	0.021	0	0.0000	61.408	-4.011
120	1	1	0.798	1	1	0.065	0	0.0000	63.129	-4.120
121	1	1	0.006	1	1	7.625	0	0.0002	24.292	-1.103
122	1	1	0.987	1	1	0.000	0	0.0000	58.896	-3.849
123	1	1	0.830	1	1	0.046	0	0.0000	55.873	-3.649
124	1	1	0.326	1	1	0.967	0	0.0000	75.225	-4.848
125	1	1	0.851	1	1	0.035	0	0.0000	62.065	-4.052
126	1	1	0.478	1	1	0.504	0	0.0000	48.718	-3.154
127	1	1	0.562	1	1	0.336	0	0.0000	68.389	-4.444
128	1	1	0.654	1	1	0.201	0	0.0000	66.231	-4.313
129	1	1	0.249	1	1	1.328	0	0.0000	78.186	-5.017
130	1	1	0.902	1	1	0.015	0	0.0000	57.262	-3.741
131	1	1	0.980	1	1	0.001	0	0.0000	58.755	-3.839
132	1	1	0.930	1	1	0.008	0	0.0000	60.498	-3.952
133	1	1	0.286	1	1	1.137	0	0.0000	43.878	-2.798
134	1	1	0.837	1	1	0.042	0	0.0000	62.341	-4.070
135	1	1	0.781	1	1	0.077	0	0.0000	63.492	-4.142
136	1	1	0.744	1	1	0.107	0	0.0000	64.265	-4.191
137	1	1	0.849	1	1	0.036	0	0.0000	62.094	-4.054
138	1	1	0.777	1	1	0.080	0	0.0000	63.575	-4.148
139	1	1	0.827	1	1	0.048	0	0.0000	62.544	-4.083
140	1	1	0.373	1	1	0.793	0	0.0000	46.233	-2.974
141	1	1	0.638	1	1	0.221	0	0.0000	66.590	-4.335
142	1	1	0.427	1	1	0.632	0	0.0000	71.995	-4.659
143	1	1	0.260	1	1	1.270	0	0.0000	77.743	-4.991
144	1	1	0.098	1	1	2.730	0	0.0000	36.454	-2.212
145	1	1	0.897	1	1	0.017	0	0.0000	57.164	-3.735
146	1	1	0.791	1	1	0.070	0	0.0000	63.275	-4.129
147	1	1	0.126	1	1	2.337	0	0.0000	37.964	-2.336
148	1	1	0.689	1	1	0.160	0	0.0000	65.449	-4.264

		Highest Group					Second Highest Group			
	Actual Group	Predicted Group	P(D>d | G=g)		P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Discriminant Scores Function 1
Case Number			p	df						
149	1	1	0.982	1	1	0.001	0	0.0000	58.785	-3.841
150	1	1	0.453	1	1	0.563	0	0.0000	71.244	-4.615
151	1	1	0.369	1	1	0.807	0	0.0000	73.765	-4.763
153	1	1	0.901	1	1	0.015	0	0.0000	61.061	-3.988
154	1	1	0.627	1	1	0.236	0	0.0000	51.896	-3.378
155	1	1	0.934	1	1	0.007	0	0.0000	60.424	-3.948
156	1	1	0.927	1	1	0.008	0	0.0000	57.738	-3.773
157	1	1	0.541	1	1	0.373	0	0.0000	68.908	-4.475
158	1	1	0.567	1	1	0.327	0	0.0000	68.260	-4.436
159	1	1	0.521	1	1	0.411	0	0.0000	69.412	-4.506
160	1	1	0.613	1	1	0.256	0	0.0000	67.170	-4.370
161	1	1	0.406	1	1	0.690	0	0.0000	72.600	-4.695
162	1	1	0.735	1	1	0.114	0	0.0000	54.054	-3.526
163	1	1	0.907	1	1	0.014	0	0.0000	57.357	-3.748
164	1	1	0.566	1	1	0.329	0	0.0000	50.644	-3.291
165	1	1	0.865	1	1	0.029	0	0.0000	56.560	-3.695
166	1	1	0.794	1	1	0.068	0	0.0000	63.231	-4.126
167	1	1	0.016	1	1	5.757	0	0.0000	27.991	-1.465
168	1	1	0.802	1	1	0.063	0	0.0000	55.338	-3.613
169	1	1	0.750	1	1	0.101	0	0.0000	54.347	-3.546
170	1	1	0.504	1	1	0.447	0	0.0000	69.862	-4.533
171	1	1	0.575	1	1	0.314	0	0.0000	68.074	-4.425
172	1	1	0.548	1	1	0.362	0	0.0000	68.747	-4.466
173	1	1	0.234	1	1	1.415	0	0.0000	78.851	-5.054
174	1	1	0.679	1	1	0.171	0	0.0000	65.663	-4.278
175	1	1	0.802	1	1	0.063	0	0.0000	63.059	-4.115
176	1	1	0.787	1	1	0.073	0	0.0000	55.054	-3.594
177	1	1	0.615	1	1	0.253	0	0.0000	51.652	-3.361
178	1	1	0.021	1	1	5.345	0	0.0000	28.924	-1.552
179	1	1	0.880	1	1	0.023	0	0.0000	61.485	-4.016
180	1	1	0.967	1	1	0.002	0	0.0000	59.785	-3.906
181	1	1	0.985	1	1	0.000	0	0.0000	58.842	-3.845
182	1	1	0.585	1	1	0.299	0	0.0000	67.845	-4.411
183	1	1	0.816	1	1	0.054	0	0.0000	55.604	-3.631
184	1	1	0.781	1	1	0.077	0	0.0000	54.947	-3.587
185	1	1	0.934	1	1	0.007	0	0.0000	57.875	-3.782
186	1	1	0.795	1	1	0.068	0	0.0000	55.204	-3.604
187	1	1	0.002	1	1	9.496	0	0.0028	21.239	-0.783
188	1	1	0.660	1	1	0.194	0	0.0000	66.099	-4.304
189	1	1	0.530	1	1	0.394	0	0.0000	69.190	-4.492
190	1	1	0.559	1	1	0.341	0	0.0000	68.460	-4.448
191	1	1	0.447	1	1	0.579	0	0.0000	71.425	-4.626
192	1	1	0.868	1	1	0.028	0	0.0000	61.723	-4.031

		Highest Group					Second Highest Group			
	Actual Group	Predicted Group	P(D>d | G=g)		P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Group	P(G=g | D=d)	Squared Mahalanobis Distance to Centroid	Discriminant Scores Function 1
Case Number			p	df						
193	1	1	0.587	1	1	0.296	0	0.0000	67.796	-4.408
194	1	1	0.935	1	1	0.007	0	0.0000	60.405	-3.946
195	1	1	0.900	1	1	0.016	0	0.0000	57.217	-3.738
196	1	1	0.521	1	1	0.412	0	0.0000	69.425	-4.506
197	1	1	0.675	1	1	0.176	0	0.0000	65.758	-4.283
198	1	1	0.206	1	1	1.603	0	0.0000	41.270	-2.598
199	1	1	0.785	1	1	0.074	0	0.0000	63.404	-4.137
200	1	1	0.663	1	1	0.190	0	0.0000	66.034	-4.300

References

Application of Classification Techniques in Business, Banking and Finance, JAI.

Asch, L, (1995): "How the RMA/Fair, Isaac Credit Scoring Model Was Built", Journal of Commercial Lending, pp 10-16.

Barclaycard Issuing Presentation – September,2004.

Barclays Globe Magazine, Issue 21, September 2003.

Bird J. et al (October 1997): "Credit Cards and the Poor"; Institute for Research on Poverty, Discussion Paper 1148-97.

Brandley, P.S., Fayyad, U.M., and Mangasarian, O.L, (Summer 1999): "Mathematical Programming For Data Mining", Formulations And The Challenges, INFORMS. Journal On Computing, Vol. No.3 pp. 120 –153.

Chandlers and Coffman (1977): "The Value of Credit Reports Versus their Costs" Proceedings of Eastern Finance Association.

Damascos, X., S. (1977): "Decision, Models for evaluation of Credit Cards: Application of the Multicreteria Method". ELECTRE TRI Master Thesis, Technical University, Crete, Chania.

Eisenbeis, R.A., (1981): "Credit-Scoring Applications". In E.I. Altman et al. (Eds.).

Greene, W.H., (1993): "Econometric Analysis": Second Edition, Macmillan.

Geer, C.C, (1967a): "The Optimal Credit Acceptance Policy". Journal of Finance and Quantitative Analysis.

Hand, D.J., (1994): "Assessing Classification Rules". J. Applied Statistics, 21 (3), pp. 3-16.

Hand, D.J. and W.E. Henley, (1997): "Statistical Classification Methods in Consumer Credit Scoring: A Review". Journal of Royal Statistical Association, Series A. 160 (3), pp. 523-41.

Leonard, K.J., (1996): "The Development of Credit Scoring Quality Measures" International Journal of Quality and Reliability Management, pp79-85.

Kennedy, P., (1998): "A Guide to Economics", Fourth Edition, MIT.

Lewis, E.M., (1990): An Introduction to Credit Scoring, Athena.

Mangasarian O., Street W. and Wolberg (1995): "Breast Cancer Diagnosis and

Prognosis Via Linear Programming". Operations Research, 43, pp. 570-577.

Mester, L.J., (1997): "What's the Point of Credit Scoring?" Federal Research Bank Of Philadelphia, Business Review, Sept./Oct., pp. 3-16.

Orlger, Y., (1975): Analytic Methods In Loan Evaluation, Lexington, Mass; Lexington Books, D. C. Health.

Reichart A. K., Cho, C-C, and Wagner G. M. (April, 1983): " An examination of Conceptual issues involved in Developing Credit Scoring Models". Journal Of Business And Economic Statistics, Vol. 1. No. 2.

Schreiner, M., (Oct.1999): "A Scoring Model Of The Risk Of Costly Arrears at Micro finance Lender in Bolivia". Micro Finance Risk Management, http://www.microfinance.com.

Scott, E. (1978): " On the financial Application of Discriminant Analysis" Journal of Financial and Quantitative Analysis, March, pp 200- 204.

Thomas L.C (2000). "A Survey Of The Credit And Behavioral Scoring: Forecasting Financial Risk Of Lending Consumers". International Journal of Forecasting, 16, pp. 149-172.

Titterington, D.M. (1992): A Discriminant Analysis And Related Topics. In Thomas L. C Crook, J.N and Edelman, Oxford University Press, Oxford, pp. 53-73.

Vapnik V. (1988): Statistical Learning Theory. John Wiley and Sons Inc.

VanHorne, J.C (1997). Financial Management and Policy, 10^{th} Edn.

Vigano, L., (1993): "A Credit Scoring Model for Development Banks: An African Case Study". Savings and Development, 17 (4), pp. 441-82.

Winginton, J., (1980): "A Note On The Comparison Of Logit And Discriminant Models Of Consumer Credit Behaviour " Journal Of Financial And Quantitative Analysis, 15 pp 757 – 766.

x ----- x ----- x