PERCEPTION OF CREDIT MANAGERS ON DEFAULT PREDICTION FACTORS FOR COMMERCIAL BANKS IN KISUMU

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A MANAGEMENT RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE A WARD OF A DEGREE OF MASTER IN BUSINESS ADMINISTRATION(MBA), SCHOOL OF BUSINESS, UNIVERSITY OF NAIROBI

NOVEMBER 2011

DECLARATION

This research project is my original work and has not been presented for any award in university.

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D61/70446/2008

The research project has been submitted for examination with our approval as the university supervisors.

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DEDICATION

This project proposal is dedicated to my wife Josephine Ochola, my children Rebecca Andeso, Esther Florence and Beatrice Grace for moral and financial support and encouragement. This research is also dedicated to Brothers and sister Dick Tom ,Owen Geofrey,Erick and Susan Not fogetting my dear parents Canon Shadrack owuor and mum Margret Owuor for encouragement given during the study period.

ACKNOWLEDGEMENT

I am deeply and sincerely grateful to my Senior Supervisors; Dr. Wanjare for his technical guidance support and inputs throughout the process of developing this research project. The frank and objective critique enhanced my struggle to make Project a success.

I appreciate the time he spent reading through this work and pointing out errors for correction. To the rest of the lecturers; Dr Josiah Aduda,Mr Jaleha ,Mr. Luther I appreciate the knowledge gained, report writing and presentation skills through individual and group assignments. Special thanks to members of my class, MBA finance for peer review of my work

My appreciation also goes to the Credit managers of commercial banks in Kisumu for the support they have accorded me so far. I thank my immediate family especially my dear wife Josephine and the children for their understanding and enduring my absence during weekends. I cannot forget Dr Vdelis nduba Steve wandiga,linet,Anne,Hongo,Vincent were and the Tb branch fraternity in Kemr/CDC for sponsorhip and moral support during my studies .Finaly i recognize all the efforts and contributions of those who in one way or another provided assistance in seeing me through this exercise.

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1.0 INTRODUCTION

1.1 BACKGROUND

Every time there is an application for credit from bank, credit card company, sacco, microfinance institution, hire purchase, and even local "kiosk" and group, the lender wants to understand the risk they take in extending credit

This risk comes in two ways: the possibility that the borrower will not pay on time and therefore affect their plans negatively and the possibility that the borrower may not eventually pay the money back and force them to write it off altogether. This is termed as credit default

Just like the lending market before the adoption of credit referencing, there exists serial defaulters; customers who secure services or products on credit, default and switch suppliers to get more credit besides repaying the outstanding debts. Every time, the term credit referencing is mentioned, what resonates in the mind of many is the dreaded concept of black listing of serial defaulters and the association with commercial banks.

According to Grover (1989) credit is an indispensable catalyst in financing the movement of commerce. Its roots go fairly deep in time and are definitely as old as the concept of trade itself. As early as 1300 BC the Babylonians were lending on the basis of getting a charge on security or collateral. Credit touches us in various ways. To some it could be a mere caress or a tickle, to others it could be a brush, to some a graze and for others a crash or a collision.

If the debt is not paid before the recovery notice is due, the loan is normally considered defaulted. However, it is relatively common that the debtor repays her/his debt after the recovery notice is due e.g. when receiving a claim from the enforcement authority. The research therefore considers defaults as bad debtors or credits issued in a particular year but remain unpaid as at when they fall due.

Credit default prediction is therefore the key to be used to open opportunities in chain stores banks, employment, hospitals, entertainment, and emergency loans from finance companies. Understanding of how to predict credit default will help lenders to access and manage their credit risk responsibly. By knowing how the credit risk is evaluated, lenders can take action that lowers their credit risk.

According to Wright, (2003) Sound lending procedures in retail financial institutions involve identifying high-risk applicants, modifying loan conditions such as security requirements, and monitoring repayments post-loan approval. For managers of credit unions, this procedure is complicated by the need to achieve balance between the institution’s social objective of improving loan accessibility so members can attain lifestyle goals and the possibility of reducing the institution’s viability through loan default. The results of Wright (2003) survey of Australian credit unions, in which 70 per cent of respondents reported experiencing some bankruptcy-related default on personal loans indicate managers do not impose more stringent lending conditions on high-risk borrowers. However, social and viability objectives could be better balanced through careful loan monitoring and timely arrears practices.

According to Bank for international Settlements (2004)The first firms to use credit scoring were credit card companies and the consumer lending divisions of commercial banks. The huge number of transactions involved in consumer credit necessitated a computer generated score to approve and service their customers in a cost effective and timely fashion.Fortunately, the credit information they needed for their statistical scorecards was readily available, much of it free. Their credit application provided data concerning employment, annual salary, home value, mortgage and other obligations. Additional data was available in consumer credit reports that were usually very comprehensive.The information required to conduct a credit appraisal for a consumer is far less than that of a business. A salary can be measured easier than a bank reference or a financial statement.

According to Howells (2008) a commercial bank is the traditional banking business of holding deposits, bundling them together as loans and operating payment mechanisms.

Since lending is associated with risks it is therefore important to be able to correctly predict credit defaults. This research studies the factors which are important to take into consideration when making credit default predictions for leading commercial banks in Kisumu. While most traditional scoring methods mainly look at financial and demographic variables this project look for behavioral variables.

1.2 STATEMENT OF THE PROBLEM

Since most of the research on predicting defaults is made by credit reporting agencies and credit institutions as a part of their ongoing business the availability of analysis of credit defaults is limited. There is some public international research on the area but they primarily focused on evaluating banks’ lending policy or looking at portfolio risk. The study looks closer at the determinants of default by looking at the impact of behavioral factors estimating default based on data from commercial Banks in Kisumu. It will not only evaluate how common, and publicly available, demographical variables such as income and age affect the probability of default but will also look into how behavioral factors, such as time of purchase, can change the probability of default. The project has a framework for analysis in which it categorizes the different variables by reason for increased risk. The categories are *direct financial ability*, *indirect financial ability* and *moral hazard*.

Though the measures which have been based on publicly available financial and demographic factors are still important, private, behavioral data related to debtors' *indirect financial ability* and *moral hazard*-behavior are even more important when trying to predict defaults.

Competition can come from the face of a computer screen with the competitor sitting in a different time zone. About the only thing in business that is a constant, is change. As the world transforms at an unprecedented pace so have the components that propel its engines. Thus a credit policy that is written without an understanding of the market and ample room for change in it and the one that is not frequently revisited could become obsolete in matter of days. With the information-age revolution, knowledge-based activities are becoming increasingly important for existence. Hence, enhancing skill-sets and knowledge is an intangible component of a credit policy.

Credit-risk evaluation is a very challenging and important problem in the domain of financial analysis. Many classification methods are in the literature to tackle this problem. The study seeks to try the method of building credit scoring models by looking at behavioral factors estimating credit default.

1.3 RESEARCH OBJECTIVES

(i) To determine and identify the debtors direct financial ability factors in default prediction

(ii) To determine and identify the debtors indirect financial ability in default prediction

(iii) To identify the moral hazard factors in default prediction

1.4 IMPORTANCE OF THE STUDY

The findings of this study are valuable to wide range of stakeholders as follows

Commercial banks - While the facilitation of consumption credits increases purchasing power and hence sales, it also includes risk taking, the risk of not getting paid in time, or not at all. Lenders, be they credit institutions or retailers, minimize risks by trying to predict defaults. Considering the vast amount of credit provided to Kenyan consumers, thus enabling them to smooth consumption, it is of great importance for social welfare to improve the lenders' ability to predict defaults. Better default predictions mean that more people can be provided with credit at a lower cost. Many lenders use some type of scoring model to try to predict who will default on their loan. The most commonly used models are developed by external credit reporting agencies and based on primarily public data sources. However, many of the larger lenders have also developed internal credit scoring models.

Credit risk management is chiefly responsible for the protection of an organization's lending assets. It must also provide internal communication to its credit representatives with policies and procedures that reduce ambiguity and allow them to best fulfill their duties.

The Government - the consequences of bad credit scoring routines or the lack of credit scoring models can prove devastating, not only to the individual firm but also to the society as a whole. The Government can use Credit default prediction in outlining the lending policies for chain stores and banks

The researcher and academicians; the research is important contribution to fundamental review of the overall framework of Credit default prediction of Commercial Banks in Kenya

Investors -Potential investors and lenders always require established credit prediction models before extending credit to individuals.

CHAPTER TWO

2.0 LITERATURE REVIEW

In this section, thestudyl evaluates the theoretical background of credit risk modeling, its purpose and some basics in the use of the models. There is review of the different types of methods used in credit risk modeling. Finally it outlines the framework chosen to structure data and the types of risk that framework is associated with.

2.1 CREDIT RISK MANAGEMENT

According to Economist intelligence unit (2007) credit has always been a vital part of commercial transactions, and important for a well functioning economy. People have become more and more dependent on credit and credit is used not only to finance large personal investments such as house purchases but also to finance other kinds of investment and even consumption. However, things have changed since the days when credit was personal, like the one between the local bank and a well known client. Nowadays, lending has become more anonymous and the debtor is rarely known to the party that takes the credit risk. This development has been enabled by the standardization of transactions and different methods have been developed to control the risk involved. When one extends a loan, the lender has to have some way of estimating the risk of default and account for this risk.

According to Altman & Saunders (2001) the method used when estimating the risk of default for personal loans is called credit scoring, and the importance of credit scoring has increased with the development of different securitization-techniques. Securitization has not only led to an even further increase in the distance between the debtor and the lender, but credit scoring is also used in the pricing of the security.

2.2 CREDIT SCORING

According to Henley and Hand (1997), before the rise of statistical methods to assess credit applications, applicants were assessed based on the lender’s previous experience of the debtor and/or the perceived credit worthiness of the applicant. In this process the lender had to rely on the judgment skill of the credit application reviewer whose perceptions often were based on accepted myths concerning good and bad debtor characteristics rather than proved relationships. As with any system based on prejudice rather than statistical observations this model has proven to give unsatisfactory results and the effects of using substandard scoring methods can be severe.

According to Bank for international Settlements (2004) the other reason for the application of credit scoring methods is the central role it has come to play in the Basel accords. The Basel accords dictate laws and regulations aimed at stabilizing the international banking system. It rests on three pillars; minimum capital requirements, supervisory review process and market discipline. In the calculation of minimum capital requirements credit risk is an important factor and the better ability one has to estimate credit risk the lower capital requirements are needed. This in turn implies a lower cost of capital and higher profitability for the firm hence an increased return to its owners. Moreover, in the increasingly interconnected financial world the ability to predict defaults accurately is of great importance to the stability of the banking system and thus to the society as a whole. In order to estimate credit risk, lenders are allowed to use default prediction models based on historical data. These ratings are based primarily on financial and demographical data such as age, income and gender as well as public records of how well a debtor handles her or his financial situation. The Basel accord has received heavy criticism for letting companies rely solely on external credit reporting agency ratings since it may result in cyclically lagging capital requirements.

According to Altman & Saunders (2001), credit scoring models are used today everywhere where credit is extended. Apart from the obvious users such as (e.g.) credit card companies, banks and other financial institutions, credit scoring methods are also used by various retailers, such as mail order companies, internet retailers and other companies extending consumer credit. Basically all companies that provide services or products which are delivered, consumed, or used before payment is made, need to be able to assess the credit worthiness of their customers. Most of the credit scoring research is made by private organizations and industry has been built around credit information and scoring of individuals. Apart from the external rating information, many lenders use different types of complementary internal scoring models to increase the accuracy of their credit default prediction.

2.3 CREDIT SCORING METHODS

According to Henley and Hand (1997) the common problems that arise when estimating score models is population drift reject inference and sample selection bias. Population drift is the tendency that population change over time as the environment in which the population is active changes. Reject inference is one of the problems that arise when you try to create new credit risk models based on accepted applicants only. Since the applications are based on previously accepted applications you cannot really tell what has happened to the applicants that are rejected. Sample selection bias is another problem that arises when you construct new models based on an unbiased Training set.

2.3.1 Review of credit scoring methods in use

According to Altman (1981) and Henley and Hand (1997) provide good introductions to the field of credit scoring methods. The first credit scoring methods and the most widely used are discriminant analysis and linear regression. They have the advantage of being fairly straightforward to use and are often included in statistical software programs. During the last 30 years a broad variety of scoring methods have been developed and in the later part of this period the technological evolution of computers and computational capacity has enabled the use of expert systems, neural networks and non-parametric methods such as the nearest neighborhoods method as well as time varying models taking the time factor into account. Below we will present the various types of methods applied to credit scoring of consumer loans.

2.3.1.1 Discriminant Analysis

According to Durand (1941) with discriminant analysis one investigates which variables discriminate between two or more naturally occurring groups. In any case the two naturally occurring groups are good and bad debtors where bad debtors are defined as debtors that default on their loans. Durand (1941) was the first to use discriminant analysis to create a scoring system that made predictions on good and bad debtors. His studies are still regarded as one of the most comprehensive, best, and statistically correct applications of discriminant analysis.

Criticism of the method has been expressed and discussed by e.g. Eisenbeis (1977, 1978) and Rosenberg and Gleit (1994), the main issue has been that a critical assumption in the model requires the members of the evaluated groups to be multivariate normally distributed. However, Reichert et al (1983) empirically showed that the assumption of normal distribution is not a critical limitation.

2.3.1.2 Regression

According to Lachennbruch (1978) regression analysis examines the relation of the dependent variable to some independent (explanatory) variables. Regression model using dummy variables produces a function which is parallel to the discriminant analysis function. According to Ewert (1969) he presented a model for evaluating risks associated with granting of trade credit which correctly classified 82% of the accounts. He also recognized the cost of misclassification but it was not included in the model.

2.3.1.3 Logistic Regression (Logit and Probit)

According to Fitzpatrick (1976), Lucas (1992) and Henley (1995) the logistic regression is theoretically a more appropriate statistical tool than linear regression analysis. Many of the conceptual and computational issues inherent in linear regression models are dealt with, e.g. the problem with negative possibility or possibility larger than one. One of the first applications of logistic regression to credit scoring was made by Wiginton (1980) who concluded that it was far better than discriminant analysis. Srinivasan and Kim (1987) and Leonard (1993) have also applied logistic regression on credit scoring. The study was, however, made on commercial loans.

2.3.1.4 Mathematical Programming Methods

According to Hand (1981), Showers and Chakrin (1981) and Kolesar and Showers (1985) the mathematical programming, or optimization, is the study of problems in which one seeks to minimize or maximise a function by choosing the values of real or integer variables from an allowed set. A typical task could be to minimise the number of incorrectly classified loan applicants. Researchers describe various mathematical programming methods used to maximise the proportion of correctly classified applicants, e.g. by using integer/linear programming

2.3.1.5 Recursive Partitioning

According to Breiman et al (1984) developed recursive partitioning that creates a decision tree that strives to correctly classify members of the population based on a dichotomous dependent variable. It was originally developed for use in life sciences as one of its most important references. However, there have also been examples of the method used in credit scoring by for example Mehta (1968) who developed a partitioning method to minimise cost and Boye et al (1992) who compared the method to discriminant analysis.

2.3.1.6 Expert Systems

According to Zocco (1985) and Davis (1987 provided more insights in development of an expert system that can be compared to the online help files readily available for software programme users. By asking questions one is guided to the correct answer, in the case of credit scoring to determine good and bad credits. One advantage of this method is that it is easy to explain why an applicant was rejected. There is however not much written in this field

2.3.1.7 Neural Networks

According to Henley and Hand (1997) describes neural networks as:

"A statistical model involving linear combinations of nested sequences of non-linear transformations of linear combinations of variables"

The application of this methodology seem to be somewhat rare

Rosenberg and Gleit (1994) described applications of neural networks to credit decisions and Davis et al (1992) compared them to alternative methods. The mixed performance of the method has made lenders skeptic about switching from functioning and well established credit scoring methods.

2.3.1.8 Smoothing Nonparametric Methods

According to Chatterjee and Barcun (1970) studied personal loan applications using this method. The most common non-parametric method is the nearest-neighborhood method which classifies applicants depending on what group they resemble most.

But Henley and Hand (1996) studied data from a large mail order company. One of the advantages is that the data is easy to update, thereby avoiding the problem with population drift. A problem with the method is the computational demand in storing the data, and the classification of applicants using a huge set of variables.

2.4 FRAMEWORK FOR ANALYSIS

Figure 1 Framework for Analysis

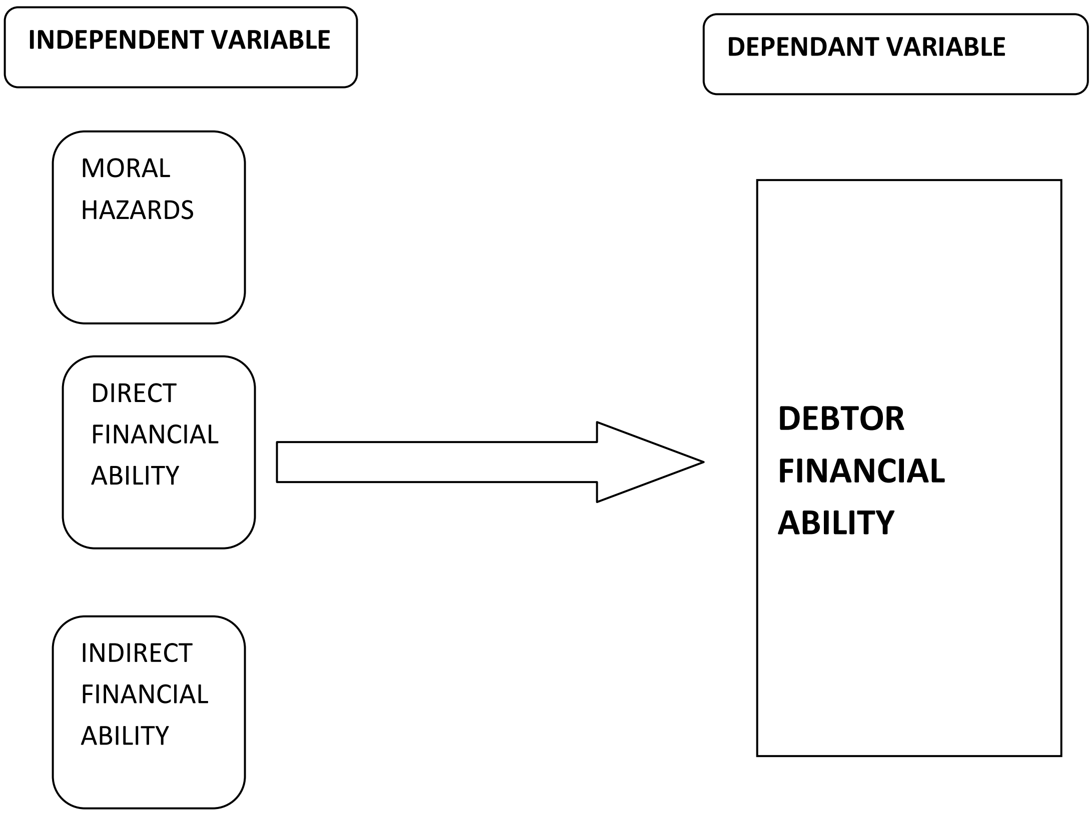

Fig 1 Own Presentation

To better understand the underlying drivers for why a debtor may default on his/her loans the research paper creates a framework for analysis in which is divided the variables into three different classes. The three classes are; characteristics that are directly indicative of a person's financial ability, characteristics that are indicative of their indirect financial ability but where they are not necessarily a clear, intuitive relationship between the dependent and independent variable, and characteristics that are related to a debtor's behavior and the concept of moral hazard. The first class consists of mainly demographical factors that tell us something about the person's financial reality.. The next two categories also include many variables that are behavioral in addition to the demographic variables that are normally used

Orgler (1971) have found that behavioral factors are generally more statistically and economically significant predictors of default than the demographical factors. The second category consists of characteristics indicative of a debtor's indirect financial ability, hence how well a person can make judgments of, manage and/or cares about her/his financial situation. A person that has been overdue on debt previously may be less financially able to make financial judgments and young people might be called credit inexperienced, these types of individuals will thus be more likely to default. Finally, there are factors that might indicate moral hazard; people assuming debt they never have the intention of paying. When a person finds himself in a situation where he is unable to pay off his debt, such a person might become self destructive and take on more debt to cover for old debt due, or simply because the marginal loss of one more crown in debt seems to be of no real value to someone that will default on a larger sum of money. In the third group forms hypotheses on variables that are e indicative of this type of behavior. This will structure the hypotheses according to those categories and this will hopefully make the paper more interesting.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 INTRODUCTION

Methodology refers to the theoretical analysis of the method appropriate to a field or the body of methods and principles particular to branch of Knowledge (Sekeran 1992) .This chapter discusses Research design applied; target population; sampling design ,Sampling data collection and analysis techniques.

3.2 RESEARCH DESIGN

The research problem can best be studied through the use of a descriptive research design. This design refers to set of methods and procedures that describe variables. It involves gathering data that describes events band then organizes, tabulates, depicts and describes the data .Descriptive studies portray the variables by answering who, what and how questions (Babbie,2002)

Mugenda and Mugenda (2003), descriptive design is a process of collecting data in order to test hypothesis or to answer the questions of current status of the subject under study. Descriptive research design is chosen because it enables the research to generalize the findings to larger population. The descriptive research design approach has been credited due to the fact that it allows analysis of the relations of variables .This enabled the researcher to evaluate the relevance and reliability factors of credit default prediction of commercial banks in Kisumu

According to Kothari, (1990), descriptive design are best suited for this kind of study where sample size is small and also structured questionnaires are used, but he recommended that to obtain data free from errors, introduced by those who are responsible from collecting them, it is necessary to closely supervise those who collect data.

Quantitative data was collected during the survey from the respondents in which the Research assistants used the structured questionnaires for self administration by the respondents. The questionnaires were used to elicit information on respondents' socio-demographic characteristics, challenges, competencies, suggestions to improve the effectiveness of credit scoring models and strategies with regards to credit default implementation.

3.3 TARGET POPULATION

The study population consisted of the credit managers and loans officers within leading commercial banks Kisumu

Currently there are 43 licensed commercial banks in Kenya according to CBK website the list out of which the details below are the names of the licensed 18 commercial banks in Kisumu

3.4 SAMPLE SIZE

Mugenda and Mugenda, (1999) further stated that the sample size must be large enough to represent the salient characteristics of the accessible population. Generally the sample size depends on factors such as the number of variables in the research, the type of research design, the method of data analysis and the size of accessible population. The study targeted 54 credit managers out of which we had 47 respondents

3.5 SAMPLING DESIGN

Sampling design is a procedure or plan drawn up before any data are collected to obtain a sample from any given population. Cooper and Schindler (2003) explained that the basic idea of sampling is, selecting some of the elements in a population, so that same conclusions can be drawn about the entire population. This results in reduced cost and greater accuracy of results.

There are 18 commercial banks and the study targeted atleast 3 managers in each of the banks this approach ensured each possible commercial bank in Kisumu to have an equal probability . The staff drawn from these commercial banks has necessary information on behavioral factors of default prediction

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3.6 RESEARCH INSTRUMENT

Mugenda and Mugenda (2003) observed that, the pre-requisite to questionnaire design is definition of the problem and the specific study objectives. The primary data was collected using structured questions and unstructured questions. The Questionnaire provided more comprehensive view than any other research tool. The entire respondents were asked the same questions in the questionnaire considering both open ended and closed ended questions. Drop and pick method was be used to distribute the questionnaires

3.7 DATA ANALYSIS TECHNIQUES

Quantitative techniques of data analysis was used to analyze the data gathered from the field. The quantitative data was entered and analyzed using statistical package for social sciences (SPSS) for windows version 12.0. Using factor analysis .The analysis employed descriptive statistics, including frequency and percentage were generated for the direct financial ability, indirect financial ability and moral hazard characteristics of the sample. Statistical significance of the association between the dependent and independent variables will be interpreted using the computation of an index that measures this relationship.

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CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the data, analyzes, the data and interprets the findings of the study. The chapter also discusses the findings in light of earlier findings. The presentation, analyses interpretation and discussion of the findings follow the four major themes of the study.

4.1.1 Questionnaire Response Rate

Data was collected from all 47 out of the 54 targeted credit manager's within the commercial banks in Kisumu. Even though the researcher did not manage to collect the data from all the Banks as required, the researcher nevertheless managed to reach 87.03% of the targeted respondents. This is in line with the findings of Coopers & Schindler (2000) who said that a questionnaire response rate of at least 75% is adequate for a study to continue.

4.2 Demographic Characteristics of Respondents

Demographic information was collected on the age, gender, and years of experience of the respondents, The results of the analyses are presented in the following subsections.

4.2.1 Distribution of the Respondents by Age

The respondents were asked to indicate the age at the time of the study in order to determine if there is a relationship between age and economic empowerment of the youth. The responses obtained are summarized in Table 4.1.

Table 4.1: Age of the Respondents

		Frequency	Percent
Valid	20-24	2	4.3
	25-29	10	21.3
	30-34	22	46.8
	35-39	7	14.9
	40-44	6	12.8
	Total	47	100.0

Table 4.1 displays the distribution of respondents by age. It shows that out of 47 respondents who participated in the study 22 (46.8.0%) of the respondents were between 30-34 years, 10 (21.3%) were aged 25 to 29 years,2(4.3%) are aged between 20 and 24 years,7 (14.9%) were aged between 34-39 years while 6 (12.8%) were over 40 years

The age distribution is uniformly distributed with the mode age group being 30 and 34 years. This shows that most credit managers are the prime age of youth are at their peak performance.

4.2.2 Distribution of the Respondents by Gender

The respondents were asked to indicate the gender at the time of the study in order to determine if there is a relationship between gender and perception on credit default . The responses obtained are summarized in Table 4.2.

Table 4.2: Gender distribution of respondents

		Frequency	Percent
Valid	Male	22	46.8
	Female	25	53.2
	Total	47	100.0

Table 4.2 presents the distribution of respondents by gender. It shows that 22 (46.8%) of the managers males are while 25 (53.2%) were females .since most banks advocates for gender balance and equality this distribution was expected because of the population distribution in the banks has more females than males.

4.2.3 Distribution of the Respondents by years of experience in banking institution

The respondents were asked to indicate their years of experience within the banking industry at the time of the study in order to determine if there is a relationship between years of experience and perception on credit default . The responses obtained are summarized in Table

Table 4.3 Years of experience of the respondents

		Frequency	Percent
Valid	< 3 years	12	25.5
	4-6	25	53.2
	7-10	7	14.9
	> 10	3	6.4
	Total	47	100.0

The table shows 12 (25.5%) of the respondents had less than 3 years of experience, 25(53.2%) had 4 to 6 years of experience,7(14.9%) of the respondents had 7 to 10 years of experience while only 3 (6.4%) had over 10 years experience

4.3 DIRECT FINANCIAL ABILITY

4. 3.1 Income levels

Out of the 47 bank managers interviewed 15 (31.9 %) of them were of opinion that high income earners were most likely to default compared to majority of the respondents who thought that high income earners were likely not to default.
In the second category of the middle income group 8(17.0) of the respondents were of the opinion that middle income earners are most likely to default on their loan while 39(83.0%)did not agree to this school of thought
In the third category for low income earners of the 12 (25.5 %) respondents agreed low income earners are most likely to default while 35(74.5%) were of the contrary opinion
It follows from the above observation that loan default has some relationship with all levels of income
When the levels of income are evaluated indepenedtly to determine whether generally there is a relationship between ability to repay loan and level of income 37(78.7%) of the respondents agreed while 10 (21.3 %) thought there is no relationship between the two variable of the contrary opinion

Table 4.4 Ability to repay loan and level of income

	Frequency	Percent
Yes	37	78.7
No	10	21.3
Total	47	100.0

4.3.3 Debt burdens

In reference to other debts burden at the time of application most of the respondents
36 (76.6%) of the respondents supported that due consideration to other debts burden should be accorded while 11 (23.4%) gave less weight to debt burden . It is then apparent that most banks give due consideration to other debts at time of loan application

4.3.4 Default probability by class of wealth

As per table 4.5 below 23(48.9%) of respondents believed weathy people have the highest probality of default while 12 (25.5%) indicated that middle class people are likely to default while the remaining 12 (25.5 %) likewisely believe low class could be leading in default

Table 4.5 wealth classification

	Frequency	Percent
Wealthy class	23	48.9
Middle class	12	25.5
Low class	12	25.5
Total	47	100.0

4.3.5 Marital status in determination of probability of default

While ranking marital status the married persons were leading in probality of default since 17(36.2%) agreed they have more commitments and are likely to be overwhelmed to the extent of them defaulting . This is closely followed by 16 (34.0%) of singles were believed to have probability of default . the divorced ,widowed and widower had a cobined 14 (29.8%) . This shows last group take their obligation with seriousness

4.4 INDIRECT FINANCIAL ABILITY

4.4.1 Age bracket for most loan applicants

From the table 4.6 below most persons are quite active at the age of 31-40 since 34 (72.3%) of the respondents supported this question , It is apparent at this age majority starts investing for the future and ends up taking a lot of credit. While 6(12.8%) were for the age between 18 years and 30years .There are 7(14.9%) respodents who also indicate ages between 41 year and 50 years

Table 4.6 Age bracket of applicants

	Frequency	Percent
18 -30	6	12.8
31-40	34	72.3
41-50	7	14.9
Total	47	100.0

4.4.2. Gender against the highest probability of default

From the data obtained 34 (72.3%) did agree that male have the highest probability of default than female who 13 (27.7%) This seem to agree with most studies outcome on gender issues

4.4.3 Residential status in default probability

Majority of persons residing in urban centres have the highest default probality with 27(57.4%) of the respondents agreed that urban centre residence have high probability of default while 20(42.6%) of respondents are of the opinion that rural folks are most likely to default

4.4.4 Default probability by regions

Ecomonic empowerement , climate conditions ,cultures and avalibility of credit forms the background of regional inbalance in deault rate . AS per table 4.7 below 19(40.4%) is the leading indicatin Nyanza province as leading in default closely followed by 11(23.4 %) for North estern . western province come s in with 10(21.3%) respondents. The remaining provinces have cumulative of 7 (14.9%)

Table 4.7 default by province

	Frequency	Percent
Nyanza	19	40.4
Western	10	21.3
Nairobi	2	4.3
Central	1	2.1
Coast	3	6.4
Eastern	1	2.1
North Eastern	11	23.4
Total	47	100.0

4.4.5. Relationship between applicant's level of education and default probality

It is apparent that there is no relationship between applicants level of education and probability of default 27(57.4%) of respondent supported the argument however 20(42.6%) of the respondents did support

4.4.6 Registered address people against default probability

Most of the respodents 30(63.8%) believed there is no relationship between loan applicants address and loan default .It is aclear indication not much significance is accorded to personal addresses as long as the applicants has one .However 17(36.2%) of the respondents thought there exist some relationship in this variable

4.4.7 The relevance of credit referencing in estimating probability of default

In table 4.8 below 30(63.8%) of respondents considered credit referencing very significant ,12 (25.5%) indicated it as significant while only 5(10.6%) of respondents thought it is insignificant in estimation of probability of default .Currently in central bank of Kenya established credit referencing agencies where most o loan default information is available for banks to make reference before advancing any low

Table 4.8 Credit referencing

	Frequency	Percent
Very significant	30	63.8
Significant	12	25.5
Insignificant	5	10.6
Total	47	100.0

4.7.8 Entrepreneurship culture and probability of default

41(87.2%) of the respondents believes entreprenurship culture has sa strong relationship with probability of default ,6(12.8%) on the contrary . If we compare this to the regional scoring in 4.4.4 above there seems to be some correlation since in area that were leading in default somehow also hold low entreprenurship culture

4.5 MORAL HAZARD

4.5.1 Provision voluntary information at the time of loan application

At the time of application most banks will require applicants to fill in some structured form and within it there is normaly a provision for additional information which is left at the discredtion of the applicant.From 40(85.1%) of the respondents this can give a rating between 41% to 100% to the applicant . However 7(14.9%) would give this variable between 1% and 40% in the ratings . It therefore follows that voluntary disclosure of information adds more scores to applicants

4.5.2 Default probability and the loan purpose

Table 4.9 loan purpose

	Frequency	Percent
Yes	34	72.3
No	13	27.7
Total	47	100.0

From the above table 4.9 34 (72.3%) of answers were indicative that loan purpose has some bearing on default . while 13(27.7%) had answers showing no correlation between loans purpose and default

4.5.3 Categories of loan purpose

Most of the respondents 23(48.9%) indicated development loans as leading in loan default,10 (21.3%) were for business,10(21.3%) were for emergency,3(6.4%) were for health issues while only 1(2.1%) was for education .The data therefore shows that development loans are the areas to keep under watch

4.5.4. loan size and the default rate

29(61.7%) of the respondents showed that loan size can increase the default rate while 18(38.3%) were to the contrary.

4.5.5 Applicants detailed contact information

There is indication of seriousness attached to detailed contact information since 26(55.3%) respondents agreed to the question while 21(44.7%) did not believe that t his variable could be an Indicator of default

4.5.6 Time of loan application and default

Depending on when banks can be approached for loan information majority of the respondents believed tha those who seek credit information at auckward times are likely to be defaulters this stood at 27(57.4%) for yes and 20(42.6%) for No

CHAPTER 5

SUMMARY ,RESULTS AND CONCLUSON

The characteristics are divided into the three groups outlined in the theory section. The first group consists of demographical factors that tell us something about the debtor's direct financial ability to repay a loan. The second group of characters shows debtor's indirect financial ability, i.e. it consists of variables indicative of a person's ability and/or willingness to make judgments and manage her/his finances. The third group of characters is related to the problem with moral hazard in lending. We hope to contribute by showing that while financial and demographical factors still are important there is much to learn from an applicant's behavior at the time of application.

5.1Direct financial ability

These variables are used in traditional credit scoring models. We would therefore expect them all to be statistically significant.

High income earners are most likely to repay their loan

All else equal a higher income increases a debtor's ability to repay a loan. It is therefore reasonable to assume that a high income would lead to lower default levels.

A high debt burden is increases probability of default

Adding more debt to an already high debt level should increase the probability of default.

Personal wealth increases the probability of default

Wealthy people will be more likely to Not to pay off their debt.

Marriage is negatively correlated with probability of default

Marriage is a proof of partnership and if one party fails to meet her/his payments, it is plausible that she/he may rely on help from her/his partner. This should reduce the risk of default. However as per the study findings it seem married persons have more debt burdens hence incurs diseconomies of scale in living together which should result in a lesser disposable income.

5.2 Indirect financial ability

The many variables used are also well known from earlier studies on credit scoring. We would thus expect them to be statistically significant and of economic relevance.

Age is relevant in determining the probability of default

From the data it obvious that we test in what way age can be used to predict the probability of default. For example one might expect a higher probability of default among younger people since they are less likely to have defaulted before and hence not screened out in the basic credit approval process. Moreover, they might be less able to make sound calculations on what kind of expenses they can handle. Hence, experience of credit, which generally increases with age, might decrease the risk of default. Finally, older people retiring from full employment might have problems to get accustomed with a lower standard of living which might lead to higher default ratios.

Men are more likely to default than women

Conventional wisdom, and to some extent previous research, says men are less risk averse than women and hence should form a riskier sub group

People from the countryside are less likely to default

Life on the countryside and in smaller societies is less anonymous than city life. The fact that people are less anonymous implies an increased insight into their financial situation. As an effect it is plausible that this would in turn imply an even greater fear of debt collectors and letters from the Enforcement Authority in the countryside than in the city, as such things might easily become public knowledge. The survey indicated they are less likely to default than persons in urban centers

People's willingness and/or ability to pay varies between regions

Although perhaps less plausible we find it interesting to investigate whether there are regional differences in the willingness or ability to pay and, hence, if the probability of default varies depending on what region people live in. Some regions, for example, could be affected by macroeconomic changes that have an impact on default rates, another explanation could be cultural differences between regions.

People's probability of default should differ depending on where there entrepreneurship culture

It seems plausible that behavior in managing loans and other types of credit in some way may be an inherited behavior connected to the values given by parents, friends and the society where one grows up.. Hence, it would be prudent to investigate if the place where you are born might have an impact on your credit worthiness.

People living on a care of-address are more likely to default

Our theory is that people that are registered on a care of-address have a less stable life situation, and possibly a weaker financial situation and therefore are more likely to default is not true

Payment history is relevant when estimating the probability of default

Past paid debt should be negatively correlated with probability of default, late payments could be an indication of both negligence and low credit worthiness but severely late payments, i.e. payments that are substantially overdue, should be strongly correlated with the probability of default. Payments on time, on the other hand, ought to indicate well run personal finances and should have a decreasing effect on the probability of default. Hence credit referencing quite significant is default estimation

5.3 Moral hazard

None of the variables below are included in traditional scoring models developed by credit reporting agencies. The main reason is that the information is not available to them. There might be internal rating models that take factors like these into consideration but we did not find any research on this area.

People that submit voluntary information are less likely to default

The reasoning behind this variable is that people that provide extra information voluntarily are more likely to have good intentions with their purchase and thus will be more likely to pay their debts.

Probability of default differ depending on loan purpose

Probability of default depends on the loan purpose .Depending on what the credit is used for, i.e. what is to be purchased; the probability of default should differ. Some loans tend to have good and more attractive purpose would thus be more attractive for people taking the “big bath”. The big bath is when someone knows they will default on their loans and try to maximize their credit. The big bath phenomenon is related to the field of behavioural economics and Kilborn (2005) provides some insights into the theories of time inconsistency etc.However, the case might also be that customer segments vary across banks and some segments attract less solid customers. In that case this variable should also be included in indirect or direct financial ability, above. Also,.

People that try to maximize their credit have a higher probability of default

Sometimes people who are denied a credit at a specific level try to obtain smaller credits. Such behaviour indicates that the person is not interested in a particular product but rather in the credit itself, this can be because the person is more or less aware that they will default and hence feel that they have nothing to lose by obtaining one more credit. Individuals with previously failed purchase attempts are thus more likely to default on their credit if it is approved.

Loan size increases probability of default

A large loan is financially more demanding than a small one, hence larger loans should increase the probability of default, however this effect, one may argue, is of marginal importance when in the debt range of 1000,0000 – 4,000,0000. More important then, is the loan size when viewed from a moral hazard perspective. As previously described people with no intentions of paying their dues may tend to maximize their credit, and this will be reflected in larger mean sums of debt in the default population than in the paying population.

People's contact information tell us something about the probability of default

The theory is that a debtor's email-address is a good indicator of how well organised lives they live and thereby a proxy for how well they may handle their personal financial situation. For example, people that have an email address connected to a broadband suppliers in general live more organised lives and are more likely to pay their bills than debtors with an anonymous email address, e.g. a hotmail address. Even when comparing to the reference of supplying no email address at all anonymous email addresses such as hotmail may be used in moral hazard situations, to be able to confirm, order and retrieve information that is often being sent by email. Moreover, many stores demand an email address to accept a purchase. People with bad intentions will avoid their work e-mail address or other e-mail addresses that are more closely connected to their identity.

People seeking loans at awkward times of the day are more likely to default

The findings indicate that people ordering at night are more likely to live a less stable life and are thus more likely to default. This combined with the more anonymous feeling of the night and the fact that more people are intoxicated at night, something that might result in poor decisions and over spending should lead to an increased default risk. As a comparison Felson and Poulsen (2003) has written about how crime is distributed over the course of the day and one can clearly see that crime rates rise during the night.

5.4 Limitations

Below we will go through limitations that were encountered during the research; the problem with sample selection bias, the inability to evaluate the estimated models, lack of relevant information and the need for specialized models.

5.4.1 Sample selection bias

. As described in the Data-section above this has also been the case with our source of data. However, this will give rise to the problem of sample selection bias in our data. The ideal data source would have included the full information on denied credit applications. Data that was not available . A way to improve the paper would have been to find a data source which included this data. It would however give rise to yet another problem; reject inference. When one denies credit there is no absolute way to determine the outcome if it had been accepted. This is a general problem when one wants to evaluate default prediction.

5.4.2 Evaluation of the model

It would have been interesting to evaluate our model. We have chosen not to, due to lack of new data to run the model on.

5.4.3 Lack of information on profitability

Lending small sums of money can be a profitable business even when loans are extended to debtors with low credit worthiness. Debtors with low credit worthiness are to a larger extent late with their payments and since this leads to fees that are high, relative to the assumed risk, the debtors can be very profitable. Developing a model that only focuses on risk, and not reward, might therefore lead to sub optimisation. This is a general problem in credit scoring models. One way to deal with this problem is to calculate the expected loss and set it in relation to expected income before credit losses. To maximise profits credits should be granted when expected income before credit losses exceeds expected credit losses. However, we did not have sufficient information to calculate the expected income for each applicant. Another factor that was hard to account for was the actual credit losses given default. Loss given default varies depending on a number of different factors including various debtor characteristics and total debt sum owed.

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5.5 Conclusion

The data analysis have shown that the explanatory power of the data collected at the time of loan application is better at explaining defaults than purely demographical data. The explanatory power in the data with behavioral parameters is a strong indicator for parameters. The comparison for the financial and demographic variables in the findings are in line with the previous research on the area.

With the rise of new technologies, new ways of applying for and extending loans have been developed. This also has implications for the development of credit scoring methods. We have looked at some variables relating to moral hazard that clearly can have a great value when predicting default. To improve credit scoring methods one needs to incorporate behavioural information indicating moral hazard and/or poor financial ability. It seems that as the application process for credits moves from the back-office of a bank directly to the internet this suddenly extends the behavioural information available. We have shown that this information can successfully be used to improve default predictions. Time of application is one of the most effective predictors of default. As the capacity and technology of today’s databases and software expand, even details such as how you move the cursor over your bank’s internet site, could prove to be valuable information. Hence, letting the applicant fill in their loan applications might have much more to it than saving time for customer service, and might in the future turn out to be essential for predicting default.

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APPEDINDICES

APPENDIX I Research Letter

APPENDIX II Letter of Transmittal

BENARD OTIENO OWUOR

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30th September , 2011

Dear Madam/Sir,

RE:RESEARCH ON PERCEPTION OF CREDIT MANAGERS ON DEFAULT PREDICTION FACTORS FOR COMMERCIAL BANKS IN KISUMU

I am a student at University of Nairobi. As part of the requirement for Master Degree in Business Administration, I am conducting research for my project on *perception of credit managers on default prediction factors for commercial banks in kisumu* . This is a prerequisite for the course in Business Administration of the School of Business of the University of Nairobi

To enable me collect data for the research, you have been selected as one of the participants of the study by virtue of your organization being commercial bank in Kisumu. Kindly complete the questionnaire. The research is for academic purposes only and thus your responses will be treated with uttermost confidentiality. You are requested to give your response as honestly as possible.

Thank you in advance for participating in this research.

Yours sincerely,

Benard Otieno Owuor

School of Business, University of Nairobi

Appendix III : Questionnaire

PERCEPTION OF CREDIT MANAGERS ON DEFAULT PREDICTION FACTORS FOR COMMERCIAL BANKS IN KISUMU

A. Respondent's Personal Data:

Your Gender: Male ☐ Female ☐

Your Age: 20-24 ☐ 25-29 ☐ 30-34 ☐ 35-39 ☐

40-44 ☐ 45-49 ☐ 50-54 ☐ > 60 ☐

Years of Experience in the banking institution:

< 3 years ☐ 4-6 ☐ 7-10 ☐ > 10 ☐

B. Direct financial ability

1. Using the scale below how would you categorize probality of default for the following income groups

(1 – Mosts likely , 2 – Very likely, 3- Likely , 4– less likely)

High income earners ☐

Middle income earners ☐

Low income earners ☐

2. Is there a relationship between ability to repay loan and level of income?

Yes ☐ No ☐

3. Taking into consideration the other debt burdens at the time of application do you think they have significant weight in determination of default

Yes ☐ No ☐

3. Between the wealthy people, middle class and low class income earners which level of income has the highest probability of default?

Wealthy people ☐ Middle class ☐ Low class ☐

4. Who among the following are most likely to default

Married ☐ Single ☐ Divorced ☐ Widowed/widower ☐

C. Indirect financial ability

1. What is the average age bracket for most loan applicants?

   18 -30 □   31-40 □   41-50 □

   51-60 □   60-70 □   > 71 □

2. Which gender has the highest probability of default?

   Male □ Female □

3. Which residential status below have higher probability of default

   Urban centre □ Rural □

4. Which province is leading in loan default?

   Nyanza □   Western □   Nairobi □   Central □

   Coast □   Eastern □   North Eastern □   Rift Valley □

5. Using the scale below can you categorize probability of default for the following regions

(1 – Mosts likely, 2 – Very likely , 3- Likely , 4– less likely)

Nyanza	1 □	2 □	3 □	4 □	5 □
Western	1 □	2 □	3 □	4 □	5 □
Nairobi	1 □	2 □	3 □	4 □	5 □
Central	1 □	2 □	3 □	4 □	5 □
Coast	1 □	2 □	3 □	4 □	5 □
Eastern	1 □	2 □	3 □	4 □	5 □
North Eastern	1 □	2 □	3 □	4 □	5 □
Rift Valley	1 □	2 □	3 □	4 □	5 □

6. Is there any relationship between applicant's level of education the probability of defaulting on loan repayment?

   Yes □ No □

7. Are people living in care of address more likely to default to default than those with registered address

   Yes □ No □

8. How relevant is credit referencing in estimating probability of default?

Very significant □ Significant □ Insignificant □

9. Is there a relationship between entrepreneurship culture and probability of default?

`Yes □ No □

D. <u>Moral hazard</u>

1. Using the scale provided below how do you consider people who provide voluntary information in terms of their probalility of default.

(1 – Yes, 2 – No 3- Not Decided)

1 □ 2 □ 3 □

2. Does default depend on the loan purpose

Yes □ No □

3. Which category of loan purpose is leading in default?

Development □ Education □ Business □ Health □ Emergency □

4. Does the loan size increase the default rate Yes □ No □

5. Applicants with detailed contact information that includes residence, email, work addresses are less likely to default.

Yes □ No □

6. Is there any relationship between time of loan application and default?

Yes □ No □

APPENDIX IV Table of Commercial Banks in Kenya

1. African Banking Corporation
2. Bank of Baroda
3. Barclays Bank of Kenya
4. Biashara Bank of Kenya
5. CFC Bank
6. Commercial Bank of Africa
7. Cooperative Bank of Kenya
8. Delphis Bank
9. Diamond Trust Bank
10. East African Development Bank
11. Habib Bank
12. Industrial Development Bank
13. Kenya Commercial Bank
14. Kenya Post Office Savings Bank
15. K-Rep Bank
16. National Bank of Kenya
17. Panafrican Bank
18. Standard Chartered Bank