THE RELATIONSHIP BETEWEEN CREDIT SCORING PRACTICES BY COMMERCIAL BANKS AND ACCESS TO CREDIT BY SMALL AND MEDIUM ENTERPRISES IN KENYA.

BY:

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THIS PROJECT IS SUBMITTED TO THE DEPARTMENT OF ACCOUNTING AND FINANCE IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION OF THE UNIVERSITY OF NAIROBI.

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DECLARATION

STUDENT DECLARATION

This research project is my original work and has not been presented for a degree in any other University.

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SUPERVISOR DECLARATION

This project has been submitted for presentation with my approval as the University supervisor.

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DEDICATION

I wish to dedicate this research project to my dear parents Mr. and Mrs. Githinji for their support and encouragement during my entire course of study. You both have been my inspiration while pursuing my dream of attaining this MBA. This achievement would not have been possible without your love and support. I also want to give a special thanks to my sister Mercy, my brothers Ben and David for your understanding and being there to give me love, support and encouragement. I am indebted to you all and may God bless you.

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ABSTRACT

Banks that have adopted credit scoring have realized significant increases in the importance of small business and micro business loans in the total lending portfolio subsequent to the use of credit scoring in the lending decision. The objective of this study was to establish the relationship between credit scoring by Kenyan banks and access to credit by SMEs in Kenya.

This was an explanatory study where the research sought to establish a relationship between the use of credit scoring and access to credit for SME loans by Kenyan banks. A census survey was conducted involving all 43 Commercial Banks in Kenya registered and licensed under the banking act as at 31st December 2009 as per the Central Bank of Kenya. This study used primary data that was collected from the respondents of the survey. Data was captured and analyzed using Statistical Package for the Social Sciences (SPSS) version 17. Regression analysis was used to determine the relationship between credit scoring and approval rates for SME's.

The study concludes that there is a relationship between credit scoring by Kenyan banks and access to credit by SMEs in Kenya. The benefits gained from the use of credit scoring include accuracy in the decision making process. This accuracy is gained to the reduction of adverse selection cases where better assessments are made in regards to an application therefore providing better decision making. The study recommends that banks need to use various credit assessment methods before availing loans to SME applicants. This in turn improves the credit scoring of banks. In addition, the banks need to regularly review their credit policies.

CHAPTER ONE
1.0 INTRODUCTION
1.1 Background to the Study

The concept of credit is one that existed and was in use almost as long as there has been civilization. It predates, by a considerable length of time the use of money, and written references to it appear as far back as in the code of Hammurabi, established around 1750 B.C. From its beginnings, credit has been used as a selling tool, to bind customers to a particular vendor and allow them to acquire more substantial goods for which they do not have the necessary capital (Mandell, 1994).

Risk is the possibility that the actual return on an investment will be different from the expected return on that investment. Credit risk has been defined as the distribution of financial losses due to unexpected changes in the credit quality of a counter party in a financial agreement. Madison (1974) posits that the oldest Mercantile Agency opened its doors in New York in 1841; it offered a new kind of service to businessmen. Earlier, in both Europe and America, businessmen seeking credit information had occasionally hired agents or organized in local associations to share information and protect themselves from credit losses. But the Mercantile Agency was the first organized effort to provide all who wished to subscribe to its service with detailed credit information about businessmen across a broad expanse of territory.

The credit granting process leads to a choice between two actions; to give the new applicant credit or to refuse. Credit scoring tries to assist this decision by finding what would have been the best rule to apply on a sample of previous applicants. This is the basis of credit scoring approach where a decision to accept or reject an application is made (Thomas et.al, 2002). It allows for case by case risk management assessment when appraising a loan application. It therefore refers to the use of statistical models to transform relevant data into numerical measures that guide credit decisions. It is therefore referred to as the industrialization of trust (Anderson, 2007). Credit scoring has been championed worldwide to be a better means of evaluating a creditworthy borrower as compared to the traditional methods of risk assessment. The development of technology over the years has seen many banks adopt credit scoring models as part of their evaluation of a creditworthy borrower. Steven (2006) posits that Credit scoring attempts to simplify the task of estimating the probability of default and calculate the loss given default from a range of complicated possible scenarios.

Miller et.al (2004), states that most credit scoring models are developed and designed to help credit grantors predict the outcome of making a loan to a business. The model is composed of several questions (characteristics) about the applicant. Different answers (attributes) are rated on a point system and assigned score weights. An applicant's score is the sum of all of his or her attribute points—the higher the score, the lower the risk. If the score is equal to or higher than the score an organization has established as the "cutoff," the applicant presents an acceptable level of risk and the institution may decide to extend credit to that applicant. In an automated system, scoring takes place instantaneously, allowing lenders to assess risk and make account origination decisions more quickly, accurately, and objectively.

Small Business Credit Scoring (SBCS) is defined as a lending technology used by many financial institutions over the last decade to evaluate applicants. It is a statistical approach to predicting the probability that a credit applicant will default or become delinquent. SBCS involves analyzing consumer data about the owner of the firm and combining it with relatively limited data about the firm itself using statistical methods to predict future credit performance. Credit information for the principal owner explains a significant amount of the variation in the performance of small business credits (Berger et al, 2005).

The objective of quantitative credit scoring is to develop models that accurately distinguish good applicants (likely to repay), from bad applicants (likely to default). Nowadays, financial institutions see their loan portfolios expand and are actively investigating various alternatives to improve the accuracy of their credit scoring practice. Even an improvement in accuracy of a fraction of a per cent might translate into significant future savings (Baesens et al, 2003). The role of Credit scoring in financial markets includes decreasing information asymmetries between borrowers and lenders. It also allows lenders to more accurately evaluate risks and improves portfolio quality. Finally, it eases adverse selection problem and lowers the cost of credit for a good borrower while increasing credit volume and improving access to credit.

Accurate credit-granting decisions are crucial to the efficiency of the decentralized capital allocation mechanisms in modern market economies. Credit bureaus and many financial institutions have developed and used credit-scoring models to standardize and automate, to the extent possible, credit decisions. From an economic point of view, increasing the efficiency of credit allocation has the effect of directing resources toward their most productive applications, increasing productivity, output, growth and fairness. From the financial institution's point of view, a small improvement in credit decisions can provide a competitive edge in a fiercely contested market, and lead to increased profits and increased probability of survival (Glenon et.al, 2008).

The term Small and Medium Enterprises (SME) covers a wide range of definitions and measures, varying from country to country. Some of the commonly used criteria are the number of employees, total net assets, sales and investment level. However, the most common definitional basis used is employment. Currently the SME Department of the World Bank works with the following definitions: Small Enterprises are defined to have up to 50 employees, with total assets and total sales of up to $3 million while Medium Enterprise is one that has up to 300 employees, having total assets and total sales of up to $ 15 million per annum (Ayyagari et al, 2003). Therefore SMEs are companies that have up to 300 employees and total assets and sales of up to $ 15 Million.

Lack of access to credit is indicated as a key problem for SMEs worldwide. In some cases, even where credit is available, the entrepreneur may have difficulties because the lending conditions may require collateral for the loan. Credit constraints operate in variety of ways in Kenya where undeveloped capital market forces entrepreneurs to rely on self-financing or borrowing from friends or relatives. Lack of access to long-term credit for small enterprises forces them to rely on high cost short term finance. For Kenyan SME's the formal banking system is too expensive and inconvenient. Whereas banks consider SMEs with no transaction history are too risky because their ability to repay loans is not yet known. These Unbanked SMEs may also not have collateral to access formal credit. Another issue is that these unbanked SMEs might not have the skills to run the business professionally. They may not have proper bookkeeping procedures, inventory systems, business plans or income statements making it hard for a bank to evaluate them (Frempong, 2007).

In Kenya by 2007, there were about 2.2 million MSME's, of which 88 percent are non-registered (Cowan et al. 2007). Of this non-registered group, only 23 percent have bank accounts, and only 10 percent have ever received credit from a formal source. Banks have a fiduciary duty to make prudent loans with their depositors' and investors' funds. Therefore, most limit their risk with the SME market either by not lending at all or by charging high interest rates and requiring at least 100-percent collateral coverage. Many SME's are reluctant to seek credit. In a survey, the vast majority of bank credit customers indicated that the costs and interest rates of getting a loan are high, it is difficult to meet the requirements for getting a loan and there is a common perception that borrowing from a formal lender will imply losing assets and property.

Though commercial banks face several problems, the main problem that the Kenyan banks have continued to face is directly related to lax credit standards for borrowers and poor portfolio risk management. SMEs have been the hardest hit in accessing credit worldwide because they are considered a high risk group. Credit scoring would provide a framework where each applicant would be ranked in accordance with their riskiness thus allowing those with good credit history to receive credit and denying those who would probably default. A credit scoring system may therefore serve to bridge this gap in provision of information and risk assessment making it easier for SME's to access formal credit.

1.2 Statement of the Problem

Banks that have adopted credit scoring have realized significant increases in small business and micro business loans in the total lending portfolio. The use of credit scoring is not universal with about 47 percent of banks surveyed using some form of credit scoring for small business lending (Cowan et al., 2006). Small firms have experienced shrinking of credit availability with the use of credit scoring (Andrew, 2005). However, small businesses in the US are not necessarily disadvantaged in accessing credit due to the use of credit scoring (Berger et al., 2005). Credit scoring therefore has the potential to offer a number of benefits which can improve access to credit for SMEs. Reichert et al (1983) is not convinced of the predictive ability of scoring approaches and finds that the benefit received from credit scoring may merely relate to the objective and efficient manner in which predictions are made. He does not believe that the scoring methods have much superiority by their own in predicting the probability of default.

Formal financial institutions in Kenya shy away from SME's because they consider them too risky and costly to serve. Lack of working capital, access to credit and access to markets for their products have been established as the major constraints that cause business closures for MSEs (Rukwaro, 2001). Information on the extent of use of credit scoring practices by banks is nonexistent. Mutie (2006) conducted a study to establish the relationship between credit scoring practices by Kenyan banks and the level of Non Performing Loans. Internationally, a study that sought to compare the use of credit scoring for small business loans and traditional lending found that the use of credit scoring increases the availability of credit for SMEs because there is an increase in the overall quality of lending (Berger et al., 2005). There however has been no study in Kenya conducted on the relationship between credit scoring and access to credit by SMEs.

Virtually all stakeholders in the Kenyan market now realize that SMEs in Kenya are the “missing middle”. Their size and demand for credit has outgrown the capacity of microfinance institutions (Mc Donald et al, 2007). It is therefore necessary to evaluate how credit scoring affects access to credit for Small and Medium Enterprises nationwide. The use of credit scoring for SME loan applications will also be established documenting the credit scoring techniques currently in use within the Commercial Banks in Kenya.

1.3 Objective of the Study

The objective of this study was to test the relationship between credit scoring by Kenyan banks and access to credit by SMEs in Kenya.

1.4 Importance of the Study

SMEs in Kenya will be able to evaluate whether the use of credit scoring models will benefit them in the long run with the adoption of credit scoring for a larger majority of banks in the country. The study may encourage SMEs to maintain good banking and repayment records so that they may have better access to credit in the future.

Commercial Banks will also benefit from the study by understanding how credit scoring impacts the accept/reject decision for SME loans. Commercial banks will learn what techniques are most prevalent in the country. The knowledge of the credit scoring practices may assist banks to better place themselves to compete for the SME market.

The academic Community will also benefit from the study because it will provide more information on the use and benefits of credit scoring as a means to reduce credit risk for banks. The study will also add to the body of knowledge about credit risk management and its practices in Kenyan banks.

CHAPTER TWO
2.0 LITERATURE REVIEW

2.1 Introduction

This section summarizes the literature that is already in existence regarding SMEs and credit scoring. It further elaborates on credit scoring techniques and the lending decision that bankers are faced with during the loan approval process.

2.2 Theoretical review

It is argued that financial development is good for growth and probably reduces income inequality. Recent studies have focused on the links between financial development and the legal institutions that can facilitate credit contracts, exploring the nature of those contracts based on the power theory of credit, information theories of credit, and the legal origin of institutions. These theories are complementary rather than alternative; they explain how legal institutions could boost financial intermediation and facilitate access to credit for a larger number of customers, some with new and small projects (McDonald et al, 2007).

2.2.1 Power Theory of Credit

The power theory of credit emphasizes that financial institutions would be more willing to extend credit if, in case of default, they could easily enforce contracts by forcing repayment or seizing collateral. The amount of credit in a country would then depend to some extent on the existence of legislation that protects the creditor rights on the quality procedures that lead to repayment. When lenders can more easily force repayment, grab collateral, or even gain control of the firm, they are more willing to extend credit (Djankov et al, 2005).

2.2.2 Information Theory of Credit

Information theories of credit refer to the amount of credit to firms and individuals would be larger if financial institutions could better predict the probability of repayment by their potential customers. Therefore, more banks know about the credit history of prospective borrowers, the deeper credit markets would be. Public or private credit registries that collect and provide broad information to financial institutions on the repayment history of potential clients are crucial for deepening credit markets. The information that each party to a credit transaction brings to the exchange will have important implications for the nature of credit contracts; the ability of credit markets to match borrowers and lenders efficiently and the role played by the rate of interest in allocating credit among borrowers. The nature of credit markets can lead to distinct roles for different types of lenders and different types of borrowers (Walsh, 2003). When lenders know more about borrowers, their credit history, or other lenders to the firm, they are not as concerned about the “lemons” problem of financing non-viable projects, and therefore extend more credit (Stiglitz et al 1981).

2.2.3 Legal Origin Theory of credit

Legal origin also has implications for financial developments. Beck et al (2004) identified a political and an adaptability channel through which legal origin affects credit markets. The political channel depends on the balance between state power and private property rights. For example, civil law that promotes institutions that favor state power over private property rights would tend to have adverse implications for the growth of credit markets. The adaptability channel recognizes that legal traditions differ in their ability to evolve efficiently because judges respond case by case to changing conditions. Both channels imply that countries whose law is French in origin should have on average slower financial development than British common law countries.

2.3 Risk

Risk can be defined as the possibility that the actual return on an investment won't be the same as the expected return on that investment.

2.3.1 Commercial Bank Risk

There are two broad risk management strategies open to banks. Banks have to identify risks individually and handle these separately referred to as risk decomposition or reduce risk by being well diversified which is referred to as aggregation (Hull, 2007).

2.3.2 Market Risk

This arises primarily from the banks trading activities due to its exposures to interest rates, exchange rates, equity prices, commodity prices and market variables. The bank aggregates the risk factors from the activities of trade and then uses this to determine the total risk faced by the bank. If the bank is well diversified, it may not be greatly affected by market risk (Hull, 2007).

2.3.3 Credit Risk

Credit risk can be attributed to the potential that any party is either unwilling to perform on an obligation or that their performance is impaired causing an economic loss to the bank. This has been managed in the past by ensuring a well diversified portfolio. The largest source of credit risk has traditionally been attributed to loans although other activities that the bank partakes in my lead to credit risk. Diversification therefore reduces this risk for banks (Hull, 2007).

2.4 Credit Risk Assessment

Berger et al (2006) suggest that the lending technologies can be grouped into four main categories: financial statement lending (based on the evaluation of information from the financial statements); asset based lending (based on the provision of collateral and its quality); credit scoring lending (based on statistical techniques); relationship lending. The first three lending techniques are usually grouped together and labeled transaction lending because the risk evaluation is based on available factual and public information, collected independently from the quality of the relationship and includes loans that are mainly spot-like and for non recurrent needs.

In support of the potential creditor's analysis of the risk-return trade-off is an assessment of the trustworthiness of the borrower. Literature on trust stresses that high levels of trust are purported to encourage trustworthy behavior and that trust can play an important role in reducing agency problems such as moral hazard and adverse selection, in cutting transaction costs (Nooteboom et al., 1997) as well as the expenses of monitoring and control. Thus, trusting relationships can benefit banks and SMEs. The benefits of increasing levels of trustworthiness could include increased credit granted.

2.4.1 Models of analyzing credit Risk

The traditional method of analyzing credit risk was based on relationship lending which took into account the 5 C's of credit (Anderson, 2007). In modern times, banks use credit scoring techniques to evaluate credit risk. Several models of credit scoring are used to determine the probability of default.

2.4.2 5 C's of credit

Banks build their credit policy around the 5 C's of credit: Character (of the applicant), Capacity to borrow, Capital (as back up), Collateral (as security), economic Condition. These assessments are based upon underwriters' own experience taking into consideration not only historical information but also the future view of the borrowers' prospects (MacDonald et al, 2006).

Character refers to as the maturity, honesty, trustworthiness, integrity, discipline, reliability and dependability of a customer. A person of good character will be open and divulge information about them in the process of the decision making. Capacity refers to the ability of a client to service his debt obligation fully. This is determined by reviewing sources of income versus obligations to determine his paying ability based on past information about borrower. Capital refers to the borrower's wealth position measured by financial soundness and market standing. The loan officer looks at what would happen if there is deterioration in the borrower's financial condition. Would they still be able to meet the debt obligation? Condition looks at the commercial, socio-economic, technological and political environment to assess the successful implementation of the project therefore the recovery of the loan issued. It looks at the sources of cash and how they vary with the business cycle and consumer demand. Collateral is a security issued to secure a loan. These guarantee the issuer of credit of a source of income in the event of failure or inability of the loan holder to pay their debt. Securities include land, building, machinery and others which may sometimes prove to be difficult to dispose in loan recovery (MacDonald et al, 2006).

2.4.3 Credit Scoring

Credit Scoring is a statistical method used to predict the probability that a loan applicant or existing borrower will default. Credit scorecards are defined as tools used to predict the behavior of new applicants based on the performance of previous applicants. Scorecards can also be used to predict the performance of existing accounts, based on past experience of accounts with similar characteristics. Credit scorecards come in two basic types, judgmental and statistical. Judgmental (also known as expert-based) scorecards are essentially a set of formal, quantitative criteria developed by incorporating the best practices and the knowledge of senior credit officers. They are especially useful for standardizing, simplifying, and speeding up decision-making. Statistical scorecards are built with data from actual loans and applications, and they have the important added benefit of quantifying the probability of default. Among statistical models, there are two basic types: generic- which is built with data from a variety of lenders and performance reported to a centralized repository such as a credit bureau, and custom- built with the performance data from a specific financial institution. A custom scorecard may use a generic score as one of its inputs (U.S. Comptroller of the Currency, 1998).

Mutie (2006), states that Credit scoring has not been widely used in business lending but that this has changed over time due to enhanced computer power and new methodologies as well as data increase. He further states that a well designed model will give a higher percentage of high scores to borrowers whose loans will perform well and higher percentage of low scores to borrowers whose loans won't perform well.

2.5 Credit Scoring Models

There are various credit scoring models in use today. They are all mathematical models used to evaluate how risky a particular borrower is.

2.5.1 Linear Probability and Logit models

This model uses past data such as accounting ratios into a model to explain repayment experience on old loans. This is then used to forecast probabilities on new loans (Abedi, 2000).

2.5.2 Risk Adjusted on Return on Capital (RAROC)

This model measures how much risk the bank is taking. It is calculated by evaluating the expected return against the value at risk. It helps to determine if returns are providing adequate compensation for risk and assesses if the bank is providing shareholders with an increase in value through participation in the business (Abedi, 2000).

2.5.3 Option Pricing Theory Models

This method starts with the observation that a borrower's limited liability is comparable to a put option written on the borrowers assets. The strike price is usually equal to the value of the debt outstanding. If in some future period, the value of the borrower's assets falls below the value of the outstanding debt, the borrower is likely to default. The probability of default here is inferred from an estimate of the firms' asset-price volatility based on the observed volatility of a firms equity prices (Abedi, 2000).

2.5.4 Neural Networks

These are artificial intelligence algorithms that allow for learning through experience to discern the relationship between borrower characteristics and the probability of default. This determines which characteristics aren’t important in determining default. This is a more flexible method since no assumptions are made about the functional form of relationship between characteristics and probability of default (Baesens et al, 2003).

2.6 Benefits of using credit scoring

Credit scoring has brought industrialization in the decision making process. The benefits gained from the use of credit scoring include accuracy in the decision making process. This accuracy is gained to the reduction of adverse selection cases where better assessments are made in regards to an application therefore providing better decision making. It has also led to an increased speed in the response system that previously took over two weeks to determine if a loan application was approved or rejected. Service delivery has also improved and it has made standardization and consistency across branches and networks. The decisions that have been made using credit scoring models have also been more objective and therefore reduced the possibility of discrimination. It has also broadened the network reach of banks where loans can be made from a distance with limited customer contact (Anderson, 2007).

2.7 Challenges of Credit Scoring

Though credit scoring is a great tool, it has its problems as well. Some of the problems include the complexity of the systems. Errors that may be made in scorecards, strategy or infrastructure may result in large losses or be difficult and expensive to rectify. There are also so many changes to the way business is done which requires significant communication with all the staff and the customers. It is also a capital intensive project that may require large capital investments to install the required infrastructure. In addition, credit scoring makes the assumption that the future will be like the past which may not be necessarily accurate (Anderson, 2007).

2.8 Empirical Evidence

Rukwaro (2001) carried out a study whose main objective was to determine how MFI's allocate credit to MSE's. The study focused on the financing aspects of MSE's, she considered some aspects of financing such as financing requirements and various sources of financing for MSE's. She found that 55% of the funds were from business income, while 15% of the funds came from friends and relatives. In addition, 10% of funding came from MFI's and 20% from personal savings. Some of the credit rationing criteria she cited included particular nature of business, location and savings as the most important factors. Proper books of accounts, no outstanding debt were relatively important as well. In conclusion, Rukwaro's study found that credit rationing and credit size are affected by the operational levels of MSE's.

Wasonga (2008) carried out a case study to determine the challenges the commercial banks face in the process of financing SME customers in Kenya. He sought out to examine how commercial banks try to address these challenges and also examine the banking needs of SME's. He found that major challenges faced by these banks included lack of banking or credit history to allow SME's to access credit from banks. SME's do not have valuable collateral to act as security for financing. Some of these SME's were also not registered and lacked financial statements required for financing. He also found that accounting was not properly done therefore they had no proper books of accounts.

In addition, Wasonga finds that banks need to come up with products that address SME needs. Banks should focus on funding for SME working capital needs. Currently, temporary overdrafts are used to finance immediate working capital needs. 60% of SME customers requested for loans ranging between Kshs. 500,000 and 1,000,000, 26.7% seek loans between Kshs. 1Million and 5 Million. Commercial banks were found to be charging various incidental costs that made the loans more expensive. The interest rates charged were between 19.75%-21%. The default rate at Fina bank was found to be very low because of the stringent methods put in place and the various collection methods used.

Frame et al. (2004) add two more dimensions to the characteristics of the likely SBCS loan recipients, income and location. They examine variation in small business loans under $100K originated in 1997 by the survey banks in each U.S. census tract. One finding is that SBCS is associated with increased lending of approximately the same magnitude in low- and moderate-income census tracts as in middle- and upper-income tracts. Another finding is that banks using SBCS lend more outside of their local markets than non-scoring banks. This is expected, given that SBCS does not require close personal contact (as in relationship lending) or much physical monitoring (as in other transactions technologies). This finding also suggests that SBCS may be associated with increased competition for credits, given that banks are not as constrained by location and, as discussed below, may raise policy questions about appropriate geographic market definitions for antitrust analysis.

Berger et al. (2005) examine the effects of using SBCS to reduce informational opacity on loan maturity. They exploit the differences in the information sets between banks that use SBCS in a form of the “discretion” manner (that use SBCS, but not to automatically approve/reject applicants) versus those that do not use SBCS at all. Thus, they test the effect of using credit scores in addition to information gathered using one of the other lending technologies in underwriting small business credits. The authors find that debt maturity is significantly longer for low-risk borrowers when they borrow from discretion banks that use SBCS to reduce informational opacity. This finding as may be viewed as additional evidence in favor of increased small business credit availability from SBCS since some borrowers are able to secure credit for longer intervals as a result of the use of this technology.

The studies by Berger (2005), find that SBCS increases small business credit availability in at least one dimension; overall quantity of lending, lending to relatively opaque, risky borrowers, lending within low-income as well as high-income areas, lending over greater distances, or increasing the maturity of loans. Interestingly, the most significant increases in credit availability appear to be due to a reduction in lending costs though the application of rules that may reduce costs, rather than a reduction in informational opacity through use of SBCS with discretion although longer loan maturities are observed for these latter institutions.

A survey conducted by Cowan et al (2006) to investigate the factors that suggest that a bank will adopt credit scoring in the U.S. provide some evidence that for those banks using credit scores, credit is being extended to a broader distribution of small business borrowers. They find that approximately 53 percent of the respondents do not use any type of credit score for originating small business loans. Lack of confidence in the scores and unique loan aspects are given as the primary reasons for not using these scores. They also find that from other responses this lack of confidence relates primarily to business credit scores that depend to some extent on self-reporting by businesses. The use of business credit scores is limited to approximately 9.5 percent of the total survey respondents. In contrast to business credit scores, the remaining 43.5 percent of banks using credit scores continue to rely predominantly on the credit score of the individual owner for purposes of originating small business loans. In addition, Cowan et al (2006) finds that many banks use credit scoring for risk based pricing and in the process make loans to lower credit quality small businesses. Credit scores enable banks to charge risk adjusted premiums on these less creditworthy loans. The ability to price loans in such a manner makes the business profitable to banks and opens opportunities for more small businesses.

Cowan et al (2006) was able to further investigate the relationship between small business lending and credit scoring. They provide empirical evidence that suggests that banks increase their investment in small business loans relative to total loans subsequent to the adoption of credit scoring for small business lending. This finding suggests a potential improvement in credit availability to small firms over time banks continue to integrate this technology in their loan underwriting. They present some encouraging data for small business owners and lenders. Rather than limiting the availability of credit, credit scoring appears to encourage lending to small businesses by providing banks with a quantifiable measure of risk. By eliminating some of the informational asymmetry inherent in these loans, credit scoring may increase the lending dollars available to small businesses. Although a more thorough investigation of the impact of credit scoring over time is needed, their results suggest that small businesses and banks alike will benefit from the integration of this technology in the lending process.

2.9 Conclusion

Despite the availability of credit scoring, the relationship of the business with the bank appears to continue to be the dominant factor considered in the lending decision. This finding is true regardless of bank size. This may reflect the value of flexibility in the renegotiation of contract terms in relationship banking. It suggests a preference for discretion based versus rules based decision making in banking. In contrast, those respondents who elected a lending methodology based on credit scoring for the most part did so to obtain a quantifiable measure of risk (Boot 2000).

Cowan et al (2006), conducted a survey of several SMEs who were bank customers in downtown Nairobi. They found that effectively developed and managed credit scoring would help meet their needs in a variety of ways. Some of the ways that credit scoring would meet their needs included: the reduction of reliance on collateral, risk-based pricing that may lower their interest rates and greater credit availability for higher-risk customers, who, without risk-based pricing, would simply be denied loans. In addition, turn-around times from application to approval and funding would likely decrease. Finally, as lenders become more confident in scoring's accuracy, risk-adjusted approval rates may increase.

In summary, SME's lack the collateral necessary collateral for financing their loans and are also subjected to higher interest rates. The average loan amount issued to SME's in Kenya is 5 Million. Credit scoring reduces informational opacity and improves the quality of lending for SME's looking to access long term financing. From the studies above, credit scoring increases the access of credit for SME's because the banks can quantify risk. However despite the availability of credit scoring in the U.S., relationship lending is still a dominant factor. Finally, Hansen et al. (2004) find evidence that suggests that SME's with access to credit grow more rapidly.

CHAPTER THREE
3.0 RESEARCH METHODOLOGY

3.1 Introduction

This section outlines how the study was conducted to show the relationship between credit scoring and the rate of approval of loans for SME's in Kenya as well as establish what the current credit scoring practices in the country were. The research design, sample and data collection methods are described to show how the research was conducted.

3.2 Research design

This was an explanatory study where the research sought to establish a relationship between the use of credit scoring and access to credit for SME loans by Kenyan banks. The study was a census survey which was conducted using a survey questionnaire which was analyzed using statistical methods. The study used a mono-method technique to collect and analyze the data. This was a cross sectional study that gave a snapshot of the current relationship of the data (Saunders et al, 2007).

3.3 The population and Sample

A census survey was conducted involving all 43 Commercial Banks in Kenya registered and licensed under the banking act as at 31st December 2009 as per the Central Bank of Kenya. Mutie (2006) conducted a census survey to establish the use of credit scoring and the level of nonperforming loans for all Kenyan banks registered at December 31st 2004.

3.4 Data Collection Methods

This study used primary data that was collected from the respondents of the survey. Data was collected through the use of detailed questionnaires issued to banks. The survey questionnaire had open ended questions where the respondents filled out short descriptive or explanatory responses. The questionnaire also had some questions that required them to pick out a choice from given selection or fill in a response if none of the responses suited them.

3.5 Data Analysis

Data was captured and analyzed using Statistical Package for the Social Sciences (SPSS) version 17. Regression analysis was used to determine the relationship between credit scoring and approval rates for SME's. The Simple linear regression model was used to determine the nature of the relationship between credit scoring and an accept/reject decision for SME loan applications. The least squares method was used to find the estimated regression equation of best fit. Further analysis was conducted on the data where the coefficient of determination was calculated to check how well the equation fit the data used. In addition, the correlation coefficient was also computed to find the strength of the linear association between the variables. The t-test was used to test for significance where the P value approach was used (Anderson et al, 2009).

The regression equation used was derived from the equation of a straight line as follows;

$$Y = \beta_o + \beta_1 x_i + e_i$$

Where;

Y was the total number of SME applications accepted at a particular bank.

x_i was the use of credit scoring at a particular bank.

β_o was the Y intercept

β_1 was the gradient of the line fitted to the data determined by the formula $\beta 1 = h/l$

e_i represented the difference between the score predicted by the line for subject *i* and the score that subject i actually obtained.

3.6 Data Reliability and Validity

Reliability is synonymous with repeatability or stability where a measurement that yields consistent results over time is said to be reliable. Reliability therefore is the degree to which measures are free from error yielding consistent results (Zickmund, 2003).One way to address the issue of reliability is to use the split half method defined as a method of measuring the degree of internal consistency by checking one half of the results of a set of scaled items against the other half. The results were numbered as the surveys were sent out and then grouped into two groups where one was the odd numbered surveys and the other even. From the two groups, the results were evaluated for internal consistency. Due to time constraints while undertaking the study it was difficult to repeat the surveys to determine repeatability of the study, however, some of the questions in the survey were repeated with slight changes in wording to evaluate the repeatability of the survey.

Validity refers to the accuracy or truthfulness of a measurement. Are we measuring what we think we are measuring is a question the researcher was to answer. There are three issues to address when evaluating the validity of a study (Zickmund, 2003). These include face, content and construct validity. Face validity refers to the likelihood that a question will be misunderstood or misinterpreted. To counter this, a pretest of the survey was carried out. Content validity refers to whether an instrument provides adequate coverage of a topic. An expert opinion was sought to verify the validity of the content.

CHAPTER FOUR

4.0 DATA ANALYSIS, PRESENTATION AND INTERPRETATION

4.1 Introduction

This chapter presents analysis and findings of the study as set out in the research methodology. The data was gathered exclusively from questionnaire as the research instrument. The questionnaire was designed in line with the objective of the study. To enhance quality of data obtained, Likert type questions were included whereby respondents indicated the extent to which the variables were practiced in a five point Likerts scale. The data has been presented in form of quantitative, qualitative followed by discussions of the data results. The chapter concludes with critical analysis of the findings.

4.2 Respondents' demographic characteristics.

4.2.1 Response Rate

The study targeted 43 respondents in collecting data. Results in table 4.1 below, show that 28 out of 43 target respondents, filled in and returned the questionnaire contributing to a 65% response rate. This response rate was good and representative and conforms to Mugenda and Mugenda (1999) stipulation that a response rate of 50% is adequate for analysis and reporting; a rate of 60% is good and a response rate of 70% and over is excellent. This commendable response rate was made a reality after the researcher aggressively administered the questionnaires. This survey can therefore be said to be successful.

Table 4.1: Response Rate

Response Rate	**Frequency**	**Percentage**
Responded	28	65
Not responded	15	35
Total	**43**	**100**

Source: Survey Data, (2010)

4.2.2 Year of establishment

The study established the year of establishment of the respondent banks. Results in table 4.2 shows that 68% of the banks were established from 1951 to 2000 while 14 percent had been established from 1910 to 1950. The remaining 18 percent had been established from 2001 to 2010.

Table 4.2 Year of establishment

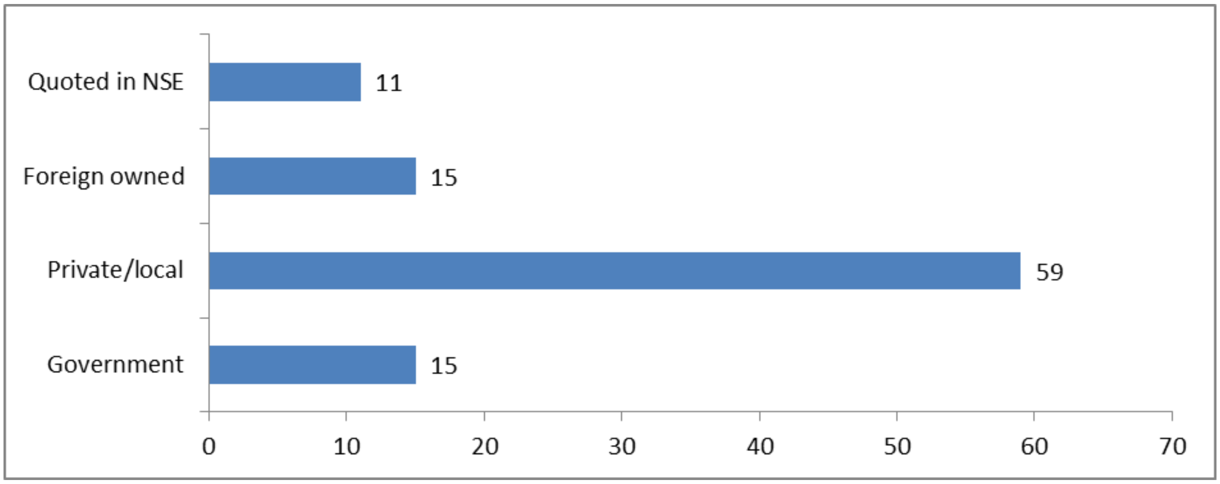
	Frequency	**Percentage**
1910-1950	4	14
1951-2000	19	68
2001-2010	5	18
Total	28	100

Source: Survey Data, (2010)

4.2.3 Ownership of the bank

The study inquired on the ownership of the banks and the results as presented in figure 4.1 shows that majority of the banks were private/local comprising 59 percent while15 percent were owned by the government and foreign owned. Only 11 percent of the banks surveyed were quoted in the NSE.

Figure 4.1 Ownership of the bank



Source: Survey Data, (2010)

4.3 SME information

4.3.1 SME Department

This section aimed at establishing whether, the banks had a specific department for SME's. Results depicted in table 4.3 shows that 71 percent of the banks surveyed had a specific SME department while 29 percent did not.

Table 4.3 Specific SME Department

	Frequency	Percent
Yes	20	71
No	8	29
Total	28	100

Source: Survey Data, (2010)

4.3.2 Year when bank opened SME department

The study inquired about the year in which the individual banks opened specialized SME departments. Results revealed in table 4.4 shows that a 60 percent of the banks had opened SME departments 5 years ago while 30 percent were opened 1 to 3 years ago. Only 10 percent opened SME departments 3 to 5 years ago.

Table 4.4 Year when bank opened SME department

Duration	Frequency	Percent
0 - 3 years	6	30
3-5 years	2	10
5 years and above	12	60
Total	20	100

Source: Survey Data, (2010)

4.3.3 How banks determine whether a company is an SME

In this section, the study aimed at establishing how the banks determined whether a company was an SME. Data from the study showed that majority of the banks considered sales turnover followed by number of employees. In addition, the cited location of an SME, its ownership and facilities were additional factors considered. The study went further to inquire about the amount of loan requested by SME's. Data presented in table 4.5 shows that majority of the respondents cited that 25% of the SME's requested Kshs 1000001-2500000, while 14 percent cited that SME's requested Kshs 50,000 – 100000. The remaining 11 percent cited that SME's requested KSh100001-250000, Kshs 100001-250000, Kshs 251000-500000, KSh2500000-5000000 and KSh5000000 and above each. Only 7 percent of the respondents cited that SME's requested loans of KShs1000-50000.

Table 4.5 Amount of loan requested by SME's

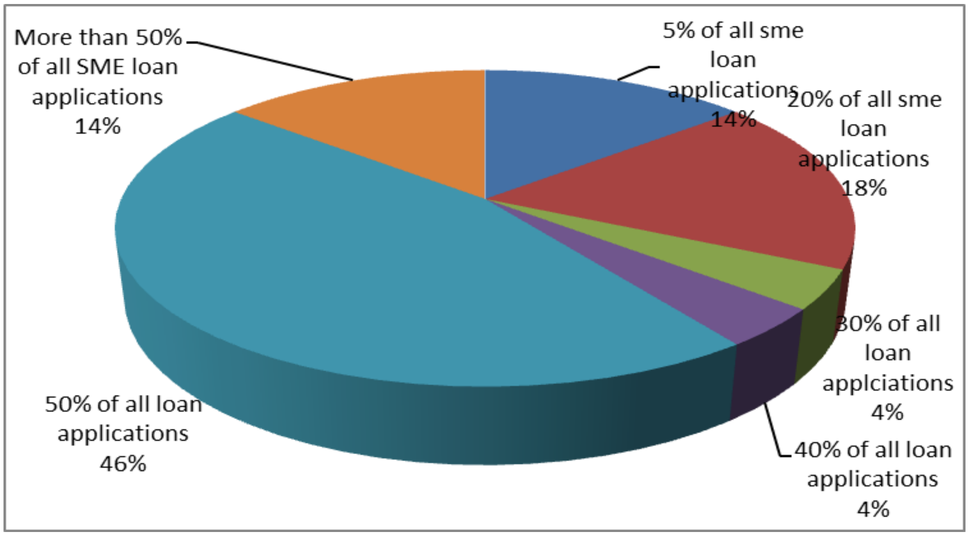
Amount	Frequency	Percent
Kshs 1000-50000	2	7
50,000 – 100000	4	14
100001-250000	3	11
251000-500000	3	11
500001-100000	3	11
1000001-2500000	7	25
2500000-5000000	3	11
5000000 and above	3	11
Total	28	100

Source: Survey Data, (2010)

4.3.4 Rate of approval for SME applications

The study further inquired the rate of approval for SME applications. Data presented in figure 4.2 shows that majority of the banks approved 50% of all SME applications comprising 46 percent while 18 percent of the banks approved 20% of all SME loan applications. 14 percent of the banks approved more than 50% of all bank applications and 5% of all SME loan applications. Banks that used credit scoring had higher approval rates (40 percent and above of all loan applications) that those that used relationship banking only. Banks that did not use credit scoring had lower approval rates of less than 40 percent of all loan applications.

Figure 4.2 Rate of approval for SME applications



Source: Survey Data, (2010)

4.3.5 Rate of approval for SME loans considered against bank expectations

In this section, the study aimed to establish the rate of approval for SME loans against bank expectations. Results revealed in table 4.6 show that 71 percent of the banks considered their approval of SME loans to be moderate against bank expectations while 18 percent had a low rate and 11 percent considered their approval rate to be higher than bank expectations.

Table 4.6 Rate of approval for SME loans considered against bank expectations

	Frequency	Percent
High	3	11
Moderate	20	71
Low	5	18
Total	28	100

Source: Survey Data, (2010)

4.3.6 Reason for rejecting loan applications

The study went further to establish the reasons for rejecting loan applications. Data revealed in table 4.7 shows that most banks rejected loan applications because of insufficient credit history and lack of sufficient collateral as was shown by 46 percent closely followed by projects not being profitable investments shown by 36 percent. The least cited reason for rejecting loan applications was age of business as was shown by 23 percent.

Table 4.7 Reason for rejecting loan applications

Reason	Yes	No
Insufficient credit history	46	54
Poor repayment on previous loan	25	75
Lack of sufficient collateral	46	54
Project not profitable investment	36	64
Age of business	23	77

Source: Survey Data, (2010)

4.4 Credit Risk Assessment

4.4.1 Credit assessment methods used to evaluate SME loan applications

The study proceeded to establish the various credit assessment methods used to evaluate SME loan applications. Results revealed in table 4.8 shows that majority of the banks used both the relationship banking and statistical methods and relationship banking only as was shown by 39 percent each while 36 percent used statistical methods only.

Table 4.8 Credit assessment methods used to evaluate SME loan applications

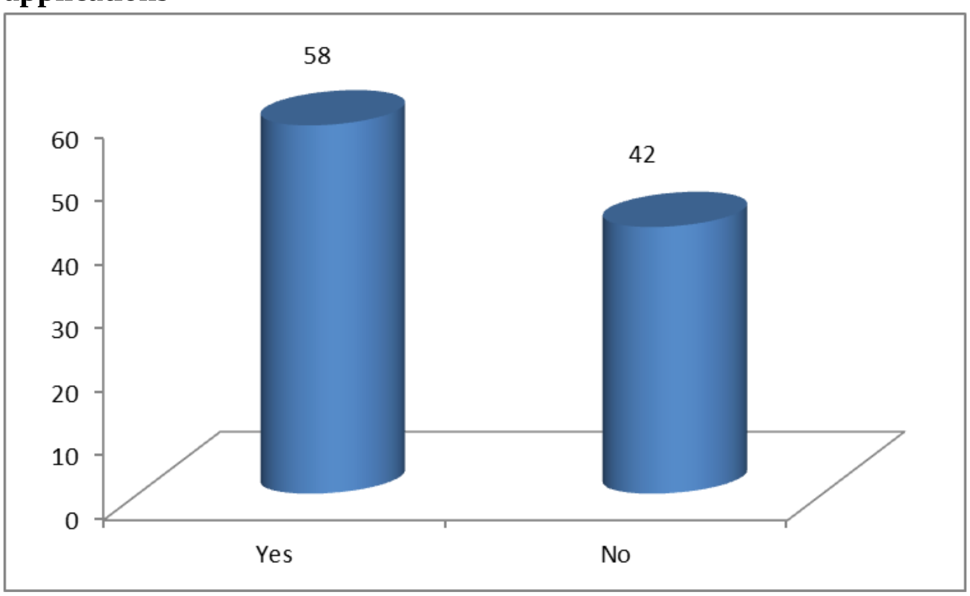
Credit assessment method	Yes	No
Relationship Banking (Human Assessment)	39	61
Statistical Methods (Credit Scoring)	36	64
Both	39	61

Source: Survey Data, (2010)

4.4.2 Use of credit scoring Models in credit risk assessment for SME loans

The study went sought to determine what credit scoring models were used in credit risk assessment for SME loan applications if any. Results revealed in figure 4.3 shows that 58 percent of the banks used a credit scoring model in credit risk assessment for SME loan applications while 42 percent did not.

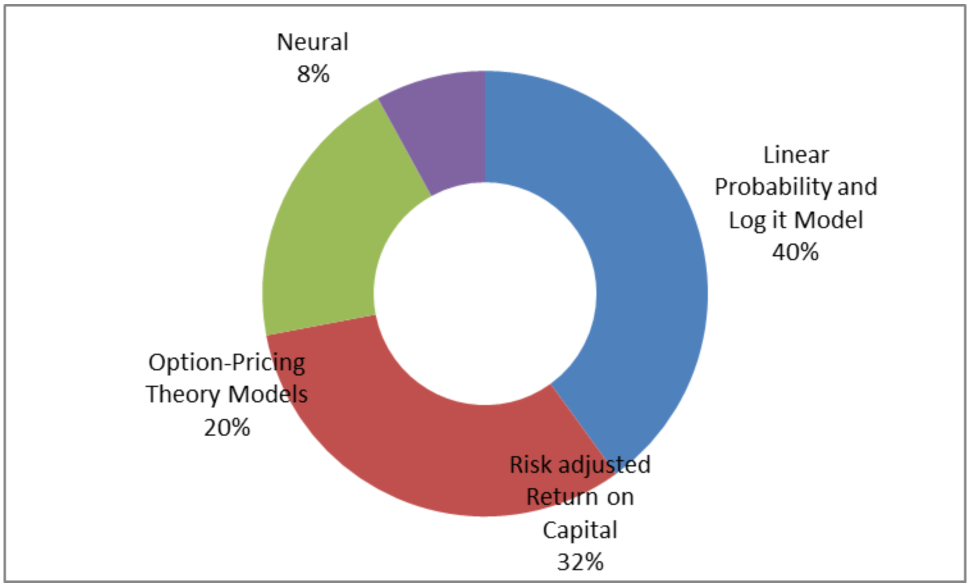
Figure 4.3 Use of Credit Scoring Model in credit risk assessment for SME loan applications



Source: Survey Data, (2010)

The study went further to establish the various credit models used in credit risk assessment for SME loan applications. Results shown in figure 4.4 shows that most banks used linear probability and log it model as was shown by 40 percent followed by 32 percent of the banks which used risk adjusted return on capital while 20 percent of the banks used option pricing theory models in credit risk assessment for SME loan applications. Only 8 percent used neural networks in credit risk assessment for SME loan applications.

Figure 4.4 Various credit models used in credit risk assessment for SME loan applications



Source: Survey Data, (2010)

4.4.3 When the bank started using the model for credit scoring

The study also sought to establish the year the banks started using a specific model for credit scoring. Table 4.8 shows that 37 percent of the banks started using models for credit scoring in the year 2009 while 21 percent in the 2008. The remaining 16 percent of banks started using credit models for credit scoring in the year 2007.

Table 4.9 When the bank started using the model for credit scoring

Year	Frequency	Percent
2009	9	37
2008	6	21
2007	4	16
2006	2	5
2005	2	5
2004-2000	5	16
Total	28	100

Source: Survey Data, (2010)

The study further inquired whether use of credit scoring models improved the credit decisions for SME loans. Results revealed in table 4.9 shows that most of the respondents agreed that using credit scoring models improved the credit decisions for SME loans as was shown by 71 percent while 29 percent cited it did not.

Table 4.10 Whether use of credit scoring models improved the credit decisions for SME loans

	Frequency	Percent
Yes	19	71
No	9	29
Total	28	100

Source: Survey Data, (2010)

4.4.4 Characteristics considered when evaluating an applicant before availing credit for SME's

The study went further to establish the various characteristics considered when evaluating an applicant before availing credit for SME's. Data in this section was analyzed using a likert scale where 1=Least important, 2 = less important, 3= moderately important, 4=

More important and 5 = Most important. Data was presented in mean and standard deviation. Results presented in table 4.10 shows that the most important characteristics considered when evaluating an applicant before availing credit for SME's was capacity to pay shown by a high mean of 4.96 followed by character of borrower shown by a mean of 4.50, collateral/security available as was shown by a mean of 3.89 and economic conditions shown by a mean of 3.78. The least cited characteristic considered when evaluating an applicant before availing credit for SME's was capital shown by a low mean of 3.68.

Table 4.11 Characteristics considered when evaluating an applicant before availing credit for SME's

	Mean	**Standard deviation**
Character of the borrower	4.5000	.96225
Capacity to pay	4.9643	.18898
Economic conditions	3.7857	.78680
Collateral/Security available	3.8929	1.06595
Capital	3.685	.7868

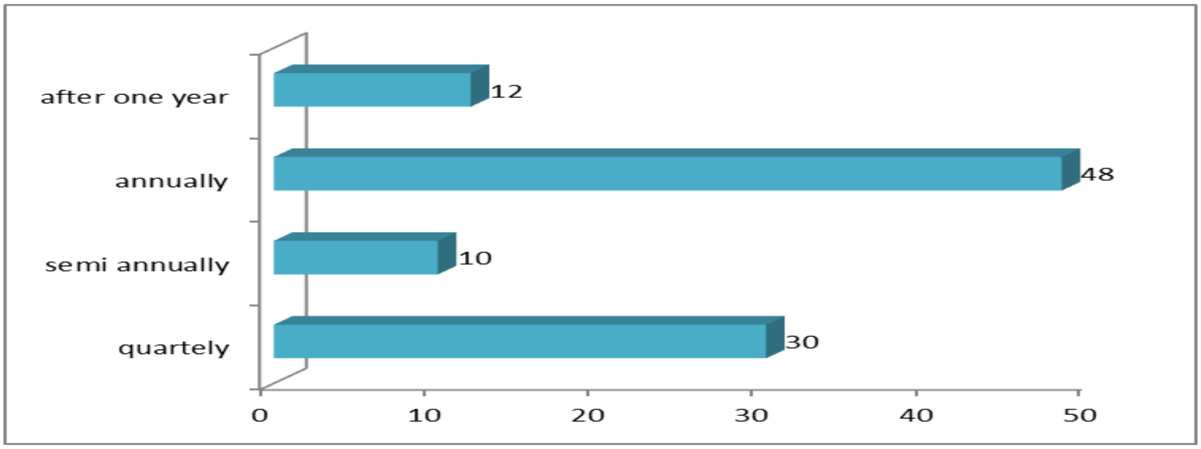
Source: Survey Data, (2010)

4.5 Credit Policy and Implementation

4.5.1 Frequency of credit policy review

The study in this section aimed at evaluating the frequency of credit policy review. Results from figure 4.5 shows that most of the banks reviewed their credit policy annually as was shown by 48 percent, while 30 percent reviewed their credit policy quarterly. 12 percent of the banks reviewed their credit policy after one year while 10 percent reviewed their credit policy semiannually.

Figure 4.5 Frequency of credit policy review



Source: Survey Data, (2010)

4.5.2 Persons involved in formulation of credit scoring models and credit policies

The study went further to establish the various persons involved in formulation of credit scoring models and credit policies. Data in this section was analyzed using a likert scale where 1=Least involved, 2 = less involved, 3= moderately involved, 4= More involved and 5 = Most involved. Data was presented after calculating the mean and standard deviation. Results presented in table 4.10 shows that senior management were the main persons involved in formulation of credit scoring models and credit policies as was shown by a high mean of 4.39, followed by credit managers and credit committees shown by a mean of 3.85 and board of directors shown by a mean of 3.46. The least involved in formulation of credit scoring models and credit policies were the branch managers as was shown by a low mean of 2.31.

Table 4.12 Persons involved in formulation of credit scoring models and credit policies

	Mean	**Standard deviation**
Senior Management	4.3929	1.28638
Board of Directors	3.4643	1.42678
Credit Managers	3.8571	1.50835
Credit Analyst	3.2143	1.61835
Credit Committee	3.8929	1.37003
Branch Manager	2.321	1.0559

Source: Survey Data, (2010)

4.5.3 Persons involved in the credit decision making for SME loans

The study went further to establish the various persons involved in formulation of credit scoring models and credit policies. Data in this section was analyzed using a likert scale where 1=Least involved, 2 = less involved, 3= moderately involved, 4= More involved and 5 = Most involved. Data was presented after calculating the mean and standard deviation. Results presented in table 4.11 shows that credit committees were the most involved in the credit decision making for SME loans as was shown by a high mean of 4.39 followed by credit managers shown by a mean of 4.25 and credit analysts shown by a mean of 3.8. The least involved in credit decision making for SME loans were board of directors as was shown by a low mean of 2.32.

Table 4.13 Persons involved in the credit decision making for SME loans

	Mean	Standard deviation
Senior Management	2.9643	1.79469
Board of Directors	2.3214	1.56474
Credit Managers	4.2500	1.26564
Credit Analyst	3.8571	1.35303
Credit Committee	4.3929	1.19689
Branch Manager	3.1071	1.34272
Loan Officer	3.321	1.4156

4.5.4 Regression analysis

Regression analysis was used to determine the relationship between credit scoring and approval rates for SME's.

Table 4.14 Coefficients

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Significance
1	(Constant)	1.570	.218		7.209	.000
	Approval rate for SME	0.24141	.045	-.323	-1.602	.123

a Dependent Variable: Use of credit scoring model

Results from table 4.12 shows that there is a relationship between use of credit scoring model and approval rate for SMEs in Kenya.

The researcher conducted a multiple linear regression analysis so as to determine the relationship between credit scoring and the three variables.

The regression equation ($Y = \beta0 + \beta1X1 + \beta2X2 + \beta3X3\ \varepsilon$) was:

$Y = 2.539273 + 0.229552X1 - 0.07023X2 + 0.082219X3 + \varepsilon$

Whereby Y = Access to credit by SMEs

X1 = Credit risk assessment

X2 = Credit scoring model

X3 = Credit policy and implementation

Unstandardized Coefficients	Standardized Coefficients	T	Significance		
	B	Std. Error	Beta		
(Constant)	2.53927	0.50667	0.87688	5.01171	1.45E-06
Credit risk assessment	0.229552	0.76767	0.25914	3.22432	0.00154
Credit scoring model	-0.0702	0.06594	-0.0818	-1.0651	0.2885
Credit policy and implementation	0.08222	0.05495	0.11989	1.49627	0.1366

According to the regression equation established, taking all constant at zero, access to credit by SME's will be 2.539273. The data findings analysed also shows that taking all other independent variables at zero, a unit increase in credit risk assessment sub-dimension will lead to a 0.229552 increase in access to credit, a unit increase in credit policy and implementation sub-dimension will lead to a 0.082219 increase in access to credit by SME's.

Table 4.15 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.985[a]	.970	.969	2.24186

Predictors: (Constant), number of applications approved where credit scoring is used

Coefficient of determination explains the extent to which changes in the dependent variable can be explained by the change in the independent variable or the percentage of variation in the dependent variable (number of applications approved) that is explained by the independent variable (the number of applications approved where credit scoring is used).

The the number of applications approved where credit scoring is used explain only 19.4% of the number of applications approved as represented by the R^2. This therefore means the the number of applications approved where credit scoring is used only contribute about 19.4% to the number of applications approved while other factors not studied in this research contributes 80.6% of the number of applications approved. Therefore, further research should be conducted to investigate the other factors (80.6%) that contribute to the number of applications approved.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.472	.955		1.542	.135
	b	0.804	.049	.985	28.842	.000

Dependent Variable: number of applications approved

The researcher conducted a multiple regression analysis so as to determine the relationship between credit scoring practices by commercial banks and access to credit by small and medium enterprises. The regression equation (**$Y = \beta_0 + \beta_1 X_1 + \varepsilon$**) will be:

Y = 1.472+0.804**X_1** +2.24186

Whereby Y = number of applications approved

X_1 = the number of applications approved where credit scoring is used

ε = Std. Error of the Estimate

According to the regression equation established, taking the number of applications approved where credit scoring is used constant at zero, the number of applications approved will be 1.472. The data findings analyzed also shows that taking all other variables at zero, a unit increase in the number of applications approved where credit scoring is used will lead to a 0.804 increase in number of applications approved. This infers that credit scoring contributed to the number of applications approved.

4.6 Summary, Findings and Implications

The study established that 60 percent of the banks reported that they opened SME departments 5 years ago, while 30 percent 1 to 3 years ago and the remaining 10 percent 3 to 5 years ago. The study established that SME's requested Kshs 1,000,001-2,500,000 comprising 25 percent while 14 percent cited that SME's requested Kshs 50,000 – 100000. The study further revealed that 46 percent of the banks approved 50% of all SME applications while 18 percent approved 20% of all SME loan applications. This shows that there is room for improvement in the approval rates for SME loans.

The study found that 71 percent of the respondents felt that the bank's approval rate for SME loans was in line with bank expectations while18 percent didn't meet bank standards. The respondents indicated that the main reasons for rejected SME applications included insufficient credit history and lack of sufficient collateral followed by projects not being profitable investments. The study further established that 39 percent of the banks used both the relationship banking and statistical methods while 36 percent used statistical methods only in credit risk assessment.

Surveyed banks reported that 58 percent of banks used a credit scoring model in the decision for SME loans while 42 percent did not. The method most preferred was linear probability and log it model in credit risk assessment, shown by 40 percent followed by 32 percent who used risk adjusted return on capital and 20 percent used option pricing theory models. The remaining 8 percent used neural models in credit risk assessment. 37 percent of the banks started using credit scoring models in 2009, while 21 percent started using credit scoring in 2000 whereas 16 percent of the banks started in the year 2007. The study further revealed that most of the respondents agreed that the use credit scoring improved the credit decision for SME loans shown by 71 percent while 29 percent cited it did not. This therefore shows that banks would benefit by using credit scoring models in their assessment for SME loans.

The most important characteristic considered when evaluating an applicant before availing credit was capacity to pay shown by a high mean of 4.96 followed by character of borrower shown by a mean of 4.50, collateral/security available with a mean of 3.89 and economic conditions shown by a mean of 3.78. The study further revealed that most of the banks reviewed their credit policy annually shown by 48 percent, while 30 percent reviewed their credit policy quarterly.

On the persons involved in formulation of credit scoring models and credit policies, senior management were the main persons involved in formulation of credit scoring models and credit policies shown by a high mean of 4.39, followed by credit managers and credit committees shown by a mean of 3.85 and board of directors shown by a mean of 3.46. The study further established that credit committees were the main group involved in the credit decision making for SME loans shown by a high mean of 4.39 followed by credit managers shown by a mean of 4.25 and credit analysts shown by a mean of 3.8. The study further established that there was a relationship between use of credit scoring model and approval rate for SMEs in Kenya where using credit scoring in the decision making process increased access to credit for SME’s by 0.804.

CHAPTER FIVE

5.0 SUMMARY, CONCLUSION AND RECCOMENDATIONS

5.1 Summary

Credit scoring is a relatively new concept in the Kenyan market where of all banks surveyed hardly any banks were using credit scoring before the year 2000. The earliest most banks used credit scoring was between the years 2000-2004. This study sought to establish a relationship between the use of credit scoring and access to credit for SME loans by Kenyan banks. Lack of access to credit for SME's has been cited as a key issue for SME's worldwide and one solution that has been offered by researchers is the use of credit scoring in the loan appraisal process.

The study was a census survey where the response rate was good and representative with 65 percent of the targeted population responding. The study found that 71 percent of banks surveyed had specific departments for SME's and that most SME loans requested were between 1,000,001-2,500,000. The study revealed that banks that used credit scoring had higher approval rates of 40 percent above those that used relationship banking only.

The main reason that banks rejected SME loan applications was of insufficient credit history. The linear probability model was the most used in credit risk assessment. 71 percent of respondents stated that use of credit scoring improved the loan decision. Regression analysis was used to find the relationship between credit scoring and access to credit for SME's and it was found that where credit scoring is used, there is a 0.804 unit increase in the number of loans approved.

5.2 Conclusions

This study revealed that the approval rate for SME loans at banks that used credit scoring was 40 percent higher than those banks that used relationship banking only. There is room for improvement in the decision making process if more banks will use credit scoring while assessing loans for SME's. The benefits gained from the use of credit scoring include accuracy in the decision making process. This accuracy is gained due to the reduction of adverse selection cases where better assessments are made in regards to an application therefore providing better decision making.

SME's will therefore benefit immensely if more banks use credit scoring in the decision making process for loan approvals. This will be one way to reduce this major problem faced by SME's in lack of access to credit. There are cost implications for banks wanting to start using credit scoring in the decision making process and therefore they should survey the market and find the best credit model to invest in. Most banks surveyed reported that they used linear probability and log it model.

Finally, banks need to be aggressive on the review of their credit policies since the market today is so versatile and to win in this market, regular review and appraisal of credit policy would see many banks ready to face any challenges that they may encounter. 48 percent of the banks surveyed reviewed their policies annually, banks should attempt to review their policies at least semi annually.

5.3 Policy Recommendations

The study recommends that banks need to use various credit assessment methods before availing loans to SME applicants. The human assessment is important in the credit decision making process as is the use of statistical methods such as credit scoring. Banks may have a better view of their clientele if both methods are used. It is however important for banks to invest in credit scoring models and train their staff to use these methods in the loan appraisal process. Banks will make better decisions if credit scoring is used and SME's will also benefit from the use of credit scoring.

Regular review of the bank's credit policies will also keep the banks prepared to face challenges and make them able to improve service delivery to clients. In addition, regular review of credit policy will allow banks to stay ahead of the competition. Banks should seek to review their credit policies at least twice a year so as to stay abreast with market demands. It may also enable them to anticipate possible changes in market trends and implement policies that will benefit their clients.

The Kenyan market is currently anticipating improvement in information sharing with the implementation of credit reference bureaus. This will over time reduce major information asymmetries that exist in the market today. However banks must respond with an internal credit scoring system so that they may be able to maximize on the gains from credit reference bureaus. In line with open communication between banks, individual banks must come up with guidelines and policies that will enable them to work with these statistical models to improve the credit granting decision process for SME's.

5.4 Limitations of the study

Local information on the use of credit scoring in Kenya and East Africa is scarce as this is a subject that has not been explored by many scholars and researchers. The information used to compile this study was mostly based on research from foreign sources who have explored this subject area in greater detail. There is only one unpublished University of Nairobi project that touched on the subject of credit scoring. Mutie (2006) explored the relationship between credit scoring and the level of non-performing loans.

This study was a cross sectional study that only gave a snapshot of the current situation. The result of this study would have yielded a different result had it taken into account the differences of approval rates over time at different banks taking into account changes in use of credit scoring. This would have required more time as most respondents would have had to go through financial reports over a number of years in order to give the appropriate responses.

5.5 Area of further study

This research study was focused on the relationship between credit scoring by Kenyan banks and access to credit by SMEs in Kenya. More research needs to be carried out in other lending institutions such as Sacco's and microfinance institutions to get more insight on various credit scoring models used in the country in relation to access to credit for SME's registered with these organizations.

This study also suggests that there are many more reasons besides the use of credit scoring that affect access to credit for SME's. This is shown by the fact that credit scoring independently only constitutes 19.4% to the number of applications approved. A study could be conducted to research into other factors that affect the approval of credit for SME's in the country.

Further analysis can also be carried out to find out which credit scoring model gives the best prediction of the probability of default for SME loans. This would give an insight into what the best credit scoring models to invest in would be especially for the banks that have not implemented credit scoring in their decision making process. Mutie (2006) looked at the relationship between the use of credit scoring and the level of non-performing loans. There are various dimensions that a researcher may test the use of credit scoring in the market today to provide more information on credit scoring uses, implications and deficiencies.

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APPENDIX A

QUESTIONNAIRE

Background Information

1. Name of Bank ………………………………………………………………………
2. Year of Establishment ……………………………………………………………….
3. Position of the respondent………………………………………………………………..
4. Ownership

   Government ( )

   Private (Local) ( )

   Foreign Owned ( )

   Quoted in the NSE ( )

SME Information

1. Does your institution have a specific department for SME's

   Yes ( ) No ( )
2. If yes, when did the department open?

   0-3 years ( )

   3-5 years ( )

   5 years and above ( )
3. How do you determine that a company is an SME?
   a. Number of employees ………………………………………………………….
   b. Sales Turnover ………………………………………………………………….
   c. Other please specify ……………………………………………………………
4. Does the bank currently use the company name or the entrepreneurs' name to process loan for SME's?

   Company name ( )

   Entrepreneur's name ( )

   Other Please specify …………………………………………………………………………
5. On average what is the amount of loan requested by SME's?

   Kshs. 1000-50,000 ( )

Kshs. 50,001- 100,000 ( )

Kshs. 100,001- 250,000 ( )

Kshs. 251,000-500,000 ( )

Kshs. 500,001-1,000,000 ( )

Kshs. 1,000,001-2,500,000 ( )

Kshs. 2,500,000-5,000,000 ( )

Kshs. 5,000,000 and above ( )

6. What is the rate of approval for SME application?

   5% of all SME loan applications ( )

   10% of all SME loan applications ( )

   20% of all SME loan applications ( )

   30% of all SME loan applications ( )

   40% of all SME loan applications ( )

   50% of all SME loan applications ( )

   Other please specify ……………………………………………………………………………

7. How is the rate of approval for SME loans considered against bank expectations?

   High ( ) Moderate ( ) Low ( )

8. Among the loan applications that were rejected, what was the main reason to reject the loan application?

   Insufficient credit history ( )

   Poor repayment on previous loan ( )

   Lack of sufficient collateral ( )

   Project not profitable investment ( )

   Age of business ( )

   Other please specify ……………………………………………………………………………

Credit Risk Assessment

1. Which of the following credit assessment methods are used to evaluate SME loan applications?

   Relationship Banking (Human Assessment) ( )

   Statistical Methods (Credit Scoring) ( )

   Both ( )

2. Do you use any Credit Scoring Model in credit risk assessment for SME loan applications?

   Yes ( ) No ( )

3. Which Credit Scoring Model do you currently use?

   Linear Probability and Log it Model ( )

   [This model uses past data to explain repayment experience on old loans as a basis to forecast default probabilities on new loans.]

   Risk adjusted Return on Capital ( )

   [This model measures how much the risk is taking. It is calculated by evaluating the expected return against the value at risk.]

   Option-Pricing Theory Models ( )

   [This method assumes that if in some future period, the value of the borrower's assets falls below the value of debt, the borrower is likely to default. The probability of default is inferred from an estimate of the firms' asset price based on the observed volatility of a firms equity prices.]

   Neural Networks ( )

   [These are artificial intelligence algorithms that allow for learning through experience to discern the relationship between borrower characteristics and the probability of default. No assumptions are made about the functional form of relationship between characteristics and probabilities of default.]

   Other ( )

   Please specify if other method used ……………………………………………………………

4. When did you start using this model for credit scoring?

   2009 ( )

2008 ( )

2007 ( )

2006 ( )

2005 ( )

2004-2000 ( )

Before 2000 ( )

5. In your opinion, does the use of credit scoring models improve the credit decision for SME loans?

   Yes ( ) No ( )

6. Has the bank used another model of Credit Scoring in the past?

   Yes ( ) No ( )

   a. If yes what method was used?

      Linear Probability and Log it Model ( )

      Risk adjusted Return on Capital ( )

      Option-Pricing Theory Models ( )

      Neural Networks ( )

      Other ( )

   Please specify if other method used ……………………………………………………………

7. Which of the following characteristics do you consider in the evaluation of an applicant before availing credit for SMEs?

Please list in order of Importance	*Least Important* 1	2	3	4	*Most Important* 5
a) Character of the borrower (Customer willingness to pay as well as past performance in repayment)	( )	( )	( )	( )	( )
b) Capacity to pay (Cash in bank, projected cash flows, financial history and business skills)	( )	( )	( )	( )	( )
c) Economic conditions	( )	( )	( )	( )	( )

(Current economic conditions and credit discipline)

d) Collateral/Security available	( )	( )	( )	( )	( )
(Total assets available)					
e) Capital	( )	( )	( )	( )	( )
(Borrowers wealth condition; Will the borrower be able to service the debt with changes in earnings?)					

Credit Policy and Implementation

1. How regularly do you review your credit policy?

   Quarterly ( )

   Semi-Annually ( )

   Annually ( )

   Other Please Specify……………………………………………………………

2. Who is involved in the formulation of credit scoring models and credit policies?

	Least Involved 1	2	3	4	Most Involved 5
Senior Management	( )	( )	( )	( )	( )
Board of Directors	( )	( )	( )	( )	( )
Credit Managers	( )	( )	( )	( )	( )
Credit Analyst	( )	( )	( )	( )	( )
Credit Committee	( )	( )	( )	( )	( )
Branch Manager	( )	( )	( )	( )	( )

Other Please Specify …………………………………………………………………

3. Who is involved in the credit decision making for SME loans?

	Least Involved 1	2	3	4	Most Involved 5
Senior Management	( )	( )	( )	( )	( )
Board of Directors	( )	( )	( )	( )	( )
Credit Managers	( )	( )	( )	( )	( )
Credit Analyst	( )	( )	( )	( )	( )
Credit Committee	( )	( )	( )	( )	( )
Branch Manager	( )	( )	( )	( )	( )
Loan Officer	( )	( )	( )	( )	( )
Other Please Specify	( )	( )	( )	( )	( )

……………………………………………………………………………………………

THANK YOU FOR YOUR TIME