Probability of Default Estimation for Commercial Lenders in Developing Economies: Creditworthiness of Consumer Borrower

Daniel Bakker
University of Eastern Africa, Baraton

Francis Odundo
Jaramogi Oginga Odinga University of Science and Technology

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Bakker Daniel K, F. Odundo & J. Nyakinda

Jaramogi Oginga Odinga University of Science & Technology

Department of Applied Statistics, Financial Mathematics & Actuarial Science

E-mail: abekadan@gmail.com

ABSTRACT

The Business of advancing credits is gradually becoming a major target for many banks, as a result there is high competition among the financial institutions leading to default of most credits. In order to raise the quality of advancing credits and reducing the risk involved thereafter, *CSM's* have been developed to improve the process of assessing credit worthiness during the credit evaluation process. Previous repayments, demographic characteristics and statistical techniques were used in constructing the *LR* model with $P(D=1)=\frac{1}{1+e^{-z}}$ to identify the important demographic characteristics related to credit risk. The results showed that *DR* is higher in males than in females. Married customers defaulted more than the singles and the higher the number of dependents, the higher the *DR*. The self-employed clients defaulted more than salary earners. Also, the higher the amount of loan collected, the higher the *PD*. With the knowledge of *LR*, it is possible to determine the credit worthiness of a borrower which may decrease bad debts, and help to set risk based credit pricing for the clients and make the credit advancing faster and more accurate.

Key words: Credit Scoring, Probability of Default, Credit Risk, Creditworthiness, Default Rate.

1 INTRODUCTION

Banking is built on the idea of profiting by loaning money to ones that are in need of money. Banks then collect interests on the payments which the borrower makes in order to pay back the money they borrowed. The likely event that some borrowers will default on their loans, that is fail to make their payments, results in a financial loss for the bank.

In the application process for new loans, banks assess the potential borrowers creditworthiness. As a measure of creditworthiness some assessment are made on the probability of default for the potential borrowers. The risk that the credit assessment of the borrowers is to modest, is called credit risk. Credit risk modeling is quite an active research field. Before the milestone of [2], credit risk on corporate loan was based on subjective analysis of credit experts of financial institutes. Probability of default is a key figure in the daily operation of any credit institute, as it is used as a measure of credit risk in both internal and external reporting.

Bank credit constitutes an important, if not, the main part of the work performed by commercial banks. Not only do credit facilities represent a sizeable portion of commercial banks assets, but they are also considered to be an important source of bank returns. However a bank's capacity to grant loans is limited as it is determined by the difference between the total number of deposits and the part kept by the bank in the form of liquid funds to meet the demands of clients [4]. Bank credit is also important because of its role in bank activities, like accepting deposits and granting loans, while at the same time observing the possibility of some clients withdrawing all or part of their deposits. In other words, the funds to be granted as credit are those which will not probably be withdrawn by depositors during the period appointed for payment of the loan [10].

Credit scoring is generally regarded as one of the more successful practical application of statistical and operations research modeling in finance and banking. Lenders use credit scoring to estimate the possible risk that results from lending money to consumers and to reduce losses from bad loans [20]. The initial step of credit scoring is to identify the predictor's variables extracted from application forms and other credit information and then to apply statistical and non-statistical techniques to produce a score which contributes to estimating credit risk. Credit scoring models have been applied to three categories; consumer loans, small business loans and corporate loans.

Over more than a decade, plenty of papers were published about credit scoring models by either studying each model individually or combining the result of different techniques [15]. Most of these papers were focused on the credit risk in developed countries [17]. Thus, it can be said that the developing countries have not been properly studied in relation to credit scoring models. This provides a good motivation for conducting research in such countries.

Credit facilities in Kenyan banks have rapidly developed to keep up with the progress made in the various economic sectors, including banking. It is expected that credit will grow to finance the various economic activities resulting from changes in the new economic structure and transformation into a market economy. Thus, the importance of credit risk models for making credit decisions has become very essential [11]. Lack of credit risk models may lead to making the wrong decision. Some of the consequences of making wrong decisions are the following:

- The unsound distribution of the banks available resources,
- The risk of credit clients being unable to repay their debt and interest,

- An increase in the debts of the borrowing bodies to banks as a result of the banks not examining financial reports in a sound manner, and
- An increase in the allowances for doubtful debts with some doubt to their sufficiency.

Lending decision of a bank is very important because it determines the future profitability and performance of the bank [6]. Recently banks are becoming more and more conscious in customer (borrower) selection to avoid the negative impact of bad loans or non-performing loans. The issue of non-performing loans (NPLs) has gained increasing attentions in the last few decades. Amounts of bad loans are alarmingly increasing in not only the developing and under-developed countries but also in developed countries. The immediate consequence of large amount of NPLs in the banking system is bank's failure as well as economic slowdown [7].

Technically higher probabilities of indebtedness imply a higher level of risk for a bank. So the selection of borrowers must depend on credit risk of the borrower. Additional to the mandatory information included in standard CRB (Credit Risk Bureau) all commercial banks in Kenya developed their own loan application form asking for some extra information (personal and financial) about the borrower to increase likelihood of an appropriate loan decision and to strengthen their risk management systems there off [19].

At the moment there is no universal scoring model that could be used by all the financial institutions, due to the fact that each institution preserves its strategy in dealing with its customers [13]. Very little has been done in terms of studying the behavioral attributes of the loan applicants in Kenya. Therefore, in this research we examined and exploited the properties of a logit model and extended its application to banking by modeling default rate in Kenyan commercial banks. The data used to construct the model was obtained from Kenya Commercial Bank, one of the Kenyan commercial banks.

1.1 Objective

The objective of this study was:

- To design a credit scoring model for individuals to assess their creditworthiness

1.2 Rationale of Study

Before offering credit to individuals, their financial position should be examined as offering loan is very risky. On the basis of the financial position of their applicants requesting credit, banks assign credit scoring and on the basis of credit scores the bank decides whether to offer the credit to these applicants and also decides the credit limits. Our research aimed to evaluate the creditworthiness of individuals by calculating their credit default probabilities via a credit scoring model.

1.3 Research Questions

The questions of the research study are as follows:

- What is the creditworthiness of individual borrowers requesting banks for loan?

- What is the risk category of individual borrowers?

2 The Model

We intend to use the Logistic Model that caters for the categorical variables in a way roughly analogous to that in which the Linear Regression

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Model is used for continuous variables. Before beginning a study of Logistic regression it is important to understand that the goal of any analysis using this method is the same as that of any model-building technique used in statistics [14]. That is to find the best credit risk model to describe the relationship between an outcome (dependent) variable and a set of independent (predictor) variables. These independent variables are often called covariates. The most common example of modeling usually used is the *linear model*, where the outcome variable is assumed to be continuous [21].

Over the last decades the Logistic regression model has become, in many fields, the standard method of analysis in this situation. What distinguishes a logistic regression model from the linear regression model is that the outcome variable in *logistic regression* is binary or dichotomous. This difference between logistic regression and linear regression is reflected both in the choice of a parametric model and in the assumptions. Once this difference is accounted for, the method employed in an analysis using logistic regression follows the same general principles used in linear regression. Thus a techniques used in linear regression analysis will motivate our approach to logistic regression.

2.1 The Logistic Model Transformation

The first difference concerns the nature of the relationship between the outcome and independent variables. In any regression problem the key quantity is the mean value of the outcome variable, given the value of the independent variable. This quantity is called conditional mean and will be expressed as $E(y|x)$ where y denotes the outcome variable and x denotes a value of the independent variable.

In linear regression we assume that this mean may be expressed as linear transformation equation of x or y such as:

$$E(y|x) = \beta_0 + \beta_1 x \tag{1}$$

Thus expression implies that it is possible for $E(y|x)$ to take on any value as x ranges between -∞ and ∞. With dichotomous data, the conditional mean must be greater than or equal to zero and less or equal to *1*. $0 \leq E(y|x) \leq 1$ shows this mean approaches *0* and *1* gradually.

The change in the $E(y|x)$ unit change in x becomes progressively smaller as the conditional mean gets to *0* or *1*. In order to simplify notation, we will use the quantity $\pi(x) = E(y|x)$ to represent the conditional mean of y given x when the *logistic regression* model:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \tag{2}$$

A transformation of $\pi(x)$ that is central to our study of logistic regression is the logit transformation. The *logit transformation* is defined, in terms of $\pi(x)$ as:

$$h(x) = \ell n \left[\frac{\pi(x)}{1 + \pi(x)} \right] = \beta_0 + \beta_1 x \tag{3}$$

The importance of this transformation is that $h(x)$ has many of the desirable properties of a linear regression model. The logit, $h(x)$, is linear in its parameters, may be continuous, and may range from $-\infty to \infty$ depending on the range of x.

The second important difference between the linear and logistic regression models, concerns the conditional distribution of the outcome variable. In *linear regression* model, we assume that an observation of the outcome variable may be expressed as $y = E(y|x) = \varepsilon$. The quantity ε is called the error and expresses an observation's deviation from the conditional mean. The most common assumption is that ε follows a normal distribution with mean of *0* and some variance that is constant across levels of the independent variable. It follows that the conditional distribution of the outcome variable given x will be normal with mean $E(y|x)$, and a variance that is constant. This is not the case with a dichotomous outcome variable. In this situation we may express the value of the outcome variable given x as:

$$y = \pi(x) + \varepsilon \tag{4}$$

where the quantity ε may assume one of two possible values.

If $y = 1$, then $\varepsilon = 1-\pi(x)$ with probability of $\pi(x)$, and if $y = 0$, $\varepsilon = -\pi(x)$, with probability $1 - \pi(x)$.

2.2 Logistic Function

Logistic function describes the mathematical form on which the logistic model is based. This function, called $f(z)$, is given by:

$$\frac{1}{1+e^{-z}}. \tag{5}$$

When plotted, the values of this function as z varies from $-\infty to \infty$ as shown in the figure, the range of $f(z)$ is between *0* and *1*, regardless of the value of z.

Considering the circle on the left side of the graph of figure below, when z is $-\infty$, the logistic function $f(z)$ equals *0*. On the right side, when z is ∞, then $f(z)$ equals *1*.

The fact that the logistic function $f(z)$ ranges between *0* and *1* is the

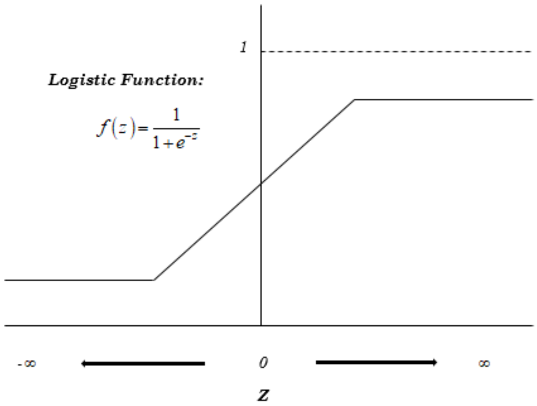

Figure 1: Logistic Function 1

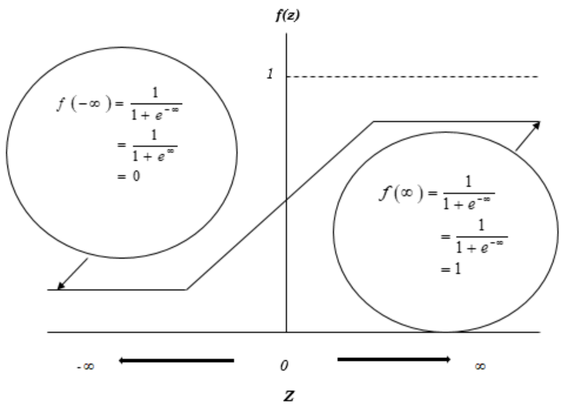

Figure 2: Logistic Function 2

primary reason the logistic model is so popular. The logistic model, is set up to ensure that whatever estimate of risk we get, it will always be some number between *0* and *1*. Therefore, for the logistic model, we can never get a risk estimate either above *1* or below *0*. This is not always true for other possible models, which is why the *logistic* model should be the first choice when a probability is to be estimated.

The shape of the *logistic* function is S. As shown below, if we start at $z = -\infty$ and move to the right, as z increases, the value of $f(z)$ closes to *0* for a while, then starts to increase dramatically toward *1*, and finally levels off around *1* as z increases toward ∞ resulting to an elongated S shaped.

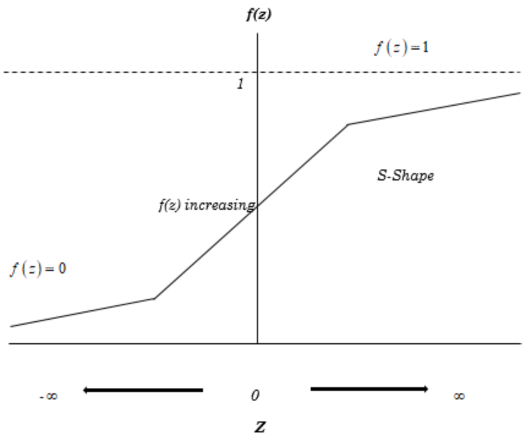

Figure 3: Logistic Function 3

2.3 Odds Vs Regression Coefficients

In the logistic regression model, the slope coefficient represents the change in the logit corresponding to a change of one unit in the independent variable, i.e.:

$$\beta_1 = h(x+1) - h(x) \tag{6}$$

where the independent variable x, is coded as either *0* or *1*.

The difference in the logit for subject when x is *1* or *0* is:

$$h(1) - h(0) = [\beta_0 + \beta_1] - [\beta_0] = \beta_1 \tag{7}$$

The first step in the interpreting the effect of a covariate in the model is to express the desired logit difference in terms of the model. In this case the logit difference is equal to β_1. The odds of an outcome being present with x is *1* is defined as:

$$\frac{\pi(1)}{1-\pi(1)} \tag{8}$$

and when x is *0* is:

$$\frac{\pi(0)}{1-\pi(0)} \tag{9}$$

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Therefore, the odds ratio denoted by OR is defined as ratio of the odds for x is *1* to x is *0* and will be given by:

$$OR = \frac{\pi(1)/[1-\pi(1)]}{\pi(0)/[1-\pi(0)]} \tag{10}$$

When the independent variable is dichotomous, then the following expression is employed:

Dependent Variable(Y)	Independent Variable(X)	
	$X = 1$	$X = 0$
$Y = 1$	$\pi(1)=\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}$	$\pi(0)=\frac{e^{\beta_0}}{1+e^{\beta_0}}$
$Y = 0$	1-$\pi(1)=\frac{1}{1+e^{\beta_0+\beta_1}}$	1-$\pi(0)=\frac{1}{1+e^{\beta_0}}$
Total	1.0	1.0

Table 1: Values of the LR Model

Substituting the values in the table to the above equation, we get:

$$\begin{aligned} OR =& \frac{\left[\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_0}}\right] \div \left[\frac{1}{1+e^{\beta_0+\beta_1}}\right]}{\left[\frac{e^{\beta_0}}{1+e^{\beta_0}}\right] \div \left[\frac{1}{1+e^{\beta_0}}\right]} \\ =& \frac{e^{\beta_0+\beta_1}}{e^{\beta_0}} \\ =& e^{\beta_0+\beta_1-\beta_0} \\ =& e^{\beta_1} \end{aligned} \tag{11}$$

This is relationship between odds ratio and the regression coefficient of a dichotomous independent variable.

2.4 Application of LR

Since odds are defined as the probability of belonging to one group divided by the probability of belonging to the other, we use the equation

$$logit(Y) = \ell n(odds) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \tag{12}$$

and

$$odds = \frac{P(Y=1)}{1-P(Y=1)} \tag{13}$$

from the above 2 equations

$$\ell n \left[\frac{P(Y=1)}{1-P(Y=1)} \right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \tag{14}$$

if we let $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k$, then the equation become:

$$\ell n \left[\frac{P(Y=1)}{1-P(Y=1)} \right] = z \tag{15}$$

Exponentiating each side of the equation we get:

$$\begin{aligned} e^{\ell n\left[\frac{P(Y=1)}{1-P(Y=1)}\right]} &= e^z \\ \frac{P}{1-P} &= e^z \\ P + Pe^z &= e^z \\ P\left[1+e^z\right] &= e^z \end{aligned} \tag{16}$$

Therefore, the probability function becomes

$$P = \frac{e^z}{1+e^z} \tag{17}$$

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Substituting the z function, we get:

$$P = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}} \tag{18}$$

Therefore it can be generalized that:

$$0 < e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k} \leq \infty \tag{19}$$

which follows that:

$$0 < \left[\frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_k x_k}}\right] \leq \infty \tag{20}$$

The estimates of the probability of having the condition Y should be between *0* and *1*.

3 Results

In this study, we considered a set of data consisting of one thousand applicants whose loans were approved within the year 2012 in Kenya Commercial Bank. The factors under study were: number of dependants, age, gender, occupation, amount of loan, marital status. The dependent variable here is called Default, which describes the customer's repayment ability. The bank definition of default is identical to the Basel II framework which states that the borrower is in default if he is more than *90* days overdue with any payment connected with the loan.The variable of interest was loan status coded as *1* for defaulters and *0* for non defaulters. Using the R programme, the following results were obtained.

Significant Factors From the above table, the significant codes specify how much significant our independent variables are, and how much significant our data-set is. These results shows that our data-set is significant as most variables have significance level over *90% (*** 99.9%, ** 99%, * 95%, . 90%)*, except from X_{16} which is insignificant.. This means that they influence the applicants' ability to repay their loans.

Table 2: Coefficients of LR

	Coefficients			
	Estimate	S.E	z-value	Pr(> | z |)
(Intercept)	-3.9191	0.9542	4.1054	4.0193e-05***
X_1	0.5863	0.0702	8.4346	<2e-16***
X_2	-0.0243	8.5844e-03	-2.8192	4.7991e-03**
X_3	0.3774	0.0886	4.3733	1.2284e-05***
X_5	-9.1345e-05	3.9679e-05	-2.3065	0.0212*
X_6	0.2364	0.0596	4.0877	4.3863e-05***
X_7	0.1622	0.0684	2.3861	0.0174*
X_8	-0.2853	0.0821	-3.4987	4.7080e-04***
X_9	0.2387	0.1140	2.0905	0.0371*
X_{10}	0.3458	0.1779	1.9453	0.0516.
X_{12}	-0.1879	0.0882	-2.1320	0.0332*
X_{14}	0.2323	0.1102	2.1130	0.0346*
X_{15}	0.3368	0.1587	2.1160	0.0343*
X_{16}	-0.2253	0.1576	-1.4311	0.1525
X_{19}	0.3391	0.1763	1.9221	0.0547.
X_{20}	1.1365	0.6110	1.8621	0.0626.

3.1 Default Rate Illustration:

The significant factors above, means that they influence the ability of the applicant to be credit worthy. Using the statistically significant factors above, we can construct our model as follows:

$$P(Y=1) = \frac{e^{-3.9191+0.5863x_1-0.0243x_2+0.3774x_3+...+0.3391x_{19}+1.1365x_{20}}}{1+e^{-3.9191+0.5863x_1-0.0243x_2+0.3774x_3+...+0.3391x_{19}+1.1365x_{20}}} \quad (21)$$

From the above model, we can calculate the probability of a customer defaulting. For example the probability of a man who has stayed with the current employer for *3* years, is married without assets and ongoing loans

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and lives in a rented house defaulting is *0.118032*. We first calculate the log odds as:

$$-3.9191+0.1622(3)+0.2387(1)-0.1879(1)+0.2323(3)+0.3368(2) = -2.0112 \tag{22}$$

We then convert the log odds to odds by taking the antilogs:

$$e^{-3.9191+0.1622(3)+0.2387(1)-0.1879(1)+0.2323(3)+0.3368(2)} = 0.1338 \tag{23}$$

We then convert the value to probability of default:

$$\frac{0.1338}{1+0.1338} = 0.118052$$

By making the relevant substitutions, the same method can be employed to calculate the probability of default of a male customer who is single is *0.14523*.

Table 3: Probability of default per gender

Gender	Odds	Probability of Default
Married Male	0.1338	0.1180
Single Male	0.1699	0.1452
Married Female	0.2157	0.1774
Single Female	0.2739	0.2149

From our model and calculations tabulated in the probability of default tables, we can deduce that, single customers default more than married customers and the longer the term, the less the chance of defaulting.

The table results show that the probability of default decreases as the term increases and The odds ratio of x_i increases as its probability increases.

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Table 4: Probability of default per loan duration

Loan Duration	Odds	Probability of Default
6	0.1157	0.1037
24	0.0745	0.0695
48	0.0417	0.0400

4 Conclusion

Out of *1000* customers who borrowed money from the bank, the default rate of men is higher than that of the women. The married borrower defaulted more than singles. Default rate increase with increasing number of dependent. People who are self employed have the highest rate of default than salary earners. With the knowledge of logistic Regression, it is possible to derive credit Risk models (logistic Regression Model) to determine the credit worthiness of a borrower.

4.1 Limitations & Recommendations

There were fundamental limitations related to research of this nature. This research selected Kenya as a developing country with a developing economy. The research results are limited to kenyan banks and such a country of its nature. This means the results may differ if the research is conducted in other country or another region with a different economy, therefore, the results have limited generalizations. Applying credit scoring models to different kenyan banks and comparing their results, would provide better scoring models for personal loans in the kenyan context of advancing loans.

This research used cross-sectional data in the credit risk models. The cross-sectional data may be attractive for they save time and are cost effective, however, the researcher's capacity is limited to address changing, developing or recommending fundamental interpretations. This thesis used loans granted in 2011 to build credit scoring models. It included characteristics that may differ from other years particularly as Kenya features in transitional economy. This may give room for time series data for future research maybe, better results can be realized. For example selection of samples across consecutive 5 or 10 years instead of 1 year could consider whether time plays an important role in building models.

Developing a support vector machine that could be competitive to the logistic regression, would provide a whole new dimension to the work done here. Neural Networks have also been shown to perform very well compared to other methods, in the developed economies. There has been some controversy about its use, but development of a neural networks credit rating model would be of great interest.

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