

COMPARATIVE ANALYSIS OF STATISTICAL MODELS IN CREDIT ASSESSMENT

BY

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DECLARATION

I hereby declare that this thesis is the result of my own research work and that no part of it has been presented for another degree in this university or elsewhere.

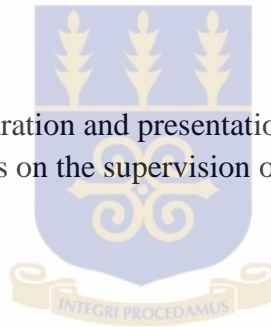
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ABSTRACT

With the emergence of the current financial crisis, important advances have been made in credit risk management. Inherent in this management process is the assessment of creditworthiness routine which subsequently leads to a credit granting decision. This study is aimed at developing a statistical model that can be used to ascertain credit assessment and to predict the probability of default of firms seeking credit from a Ghanaian commercial bank. Subsequently, an attempt was made to find financial ratios that can best be made used to successfully construct the model. To achieve these purposes, the study employed the Probit and logit models for comparative reasons in terms of their predictive abilities. Performance of the models was assessed using the percentage correctly classified (PCC) and the area under the receiver operating characteristics curved (AUC) where significant differences between the two models were observed. It was found that both the Probit and the logit classifiers yield very good performance rates but the logit model performed better for credit scoring. It was also found that ratios bordering on assets to liability ratios, account receivable to liability, Cash to Assets, current liability to total liabilities, Net current asset, and total asset firm size are those that were significantly helpful in scoring credit applicant. Practically the model assist in reducing the time spent on evaluating credit applicant of each firm subject to the model and also serve as a difference between application serving and portfolio management. Indeed the multiplier effect will be a significant improvement in loan portfolio quality of the model user.

DEDICATION

To God Almighty ,in whom lies all the treasures of wisdom and knowledge .



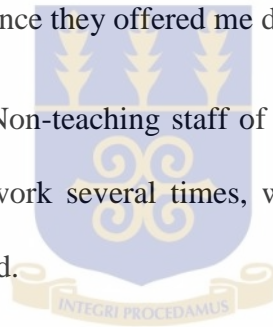
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LIST OF ABBREVIATIONS

ANN – Artificial Neural Network

AUC – Area Under receiver operating Curve

BCB – Basel Committee on Banking and Supervision

BPN – Back-propagation Neural Network

CBR – Case Based Reasoning

CRM – Credit Risk Management

DEA – Data Envelopment Analysis

DR – Delay Rejection

EAD – Exposure At Default

EL – Expected Loss

EWE – Early Warning Systems

FICO – Fair Isaac Company

GLM – Generalised Linear Model

INLA – Integrated Nested Laplace Approximation

IRB – Internal Rating Base

LDA – Linear Discriminant Analysis

LGD – Loss Given Default

LPM – Linear Probability Model

LR – Likelihood Ratio

MCMC – Marker Chain Monte Carlo

MCR – Minimum Capital Requirement

MDA – Multiple Discriminant Analysis

PCC – Percentage Correctly Classified

PCP – Percentage Correctly Predicted

PD – Probability of Default

ROA – Return on Assets

ROC – Receiver Operating Curve

RSBL – Random Space Binary Logit

SME – Small and Medium Scale

Std. Dev – Standard Deviation

Std. Err – Standard Error

SVM – Sub-vector Machines

SWOT - Strength Weaknesses Opportunity and Threats

VIF – Variance Inflation Factor test

CHAPTER ONE

1.0 INTRODUCTION

This chapter of the study brings to light the general overview of the research. Also embedded in this chapter are: the statement of the research problem, objectives of the research, rationale, scope and limitation and organisation of the research

1.1 Background to the study

Credit risk assessment is a significant area of financial management which is of major interest to practitioners and researchers. On a daily basis credit analysts have to investigate an enormous volume of financial and non-financial data of consumer credit, estimate the corresponding credit risk, and finally make crucial decisions regarding the issuance of credit (Ruparel,1990).

Embedded in this assessment process is the risk identification ,measurement and assessment process of borrowers (Santomero,1997).These aspects of credit risk assessment systems are deemed crucial in the view of the fact that credit risk emanates from the probability of default of borrowers(Doumpos et al.,2002). This is the risk of loss due to a debtor's non-payment of a loan or other line of credit. Notwithstanding, actual default occurs when a debtor fails to fulfil his or her contractual obligation according to a debt contract or has violated a loan covenant of debt agreement(Chen et al.,2010). This therefore places a major task on credit granting decision process(credit worthy assessment) which requires a distinct attention in order to properly segregate credit worthy borrowers from unworthy ones(Abdou and Pointon,2009) more so when poor loan quality is believed to have its roots in the loan information process mechanism(Richard et al., 2008)

Considerable attention has been devoted in the field of credit assessment from the theoretical points of view during the last three decades. Financial and operational researchers have tried to relate the characteristics of a firm, that is financial ratios and strategic variables to its credit risk assessment. According to this relationship the components of credit risk are identified and decision models are developed to assess credit risk and the corresponding creditworthiness of firms or individuals as accurately as possible. Decisions regarding credit risk assessment concern the evaluation of the firms' financial and non-financial characteristics in order to make optimal decisions which incorporate a tradeoff between the potential risk of loss and the probability of profits from granting credit (Srinivasan and Kim,1987)

According to Anderson (1984) , Credit-granting decisions are usually realized by credit analysts as sorting or classifying the firms seeking financing from banks or credit institutions into categories according to their creditworthiness and insolvency . Also during credit assessment evaluation process there are two major challenges which are usually encountered; the first one concerns a plethora of factors which should be examined. Factors which affect the assessment of credit include the financial characteristics of firms, strategic variables of qualitative nature which affect the general operation of the firm and its relation with the market, and even macroeconomic factors which are inflation, interest rates, and others. The credit analysts have to identify the most relevant factors for credit risk evaluation, and focus their further analysis on the examination of these factors and the second concerns, the aggregation of the factors which have been selected in the previous phase, in order to make a final decision modelling.

Dillon and Goldstein (1984) asserted in their studies on credit assessment that, factors affecting credit risk assessment lead to conflicting results and decisions. The credit analysts, when

performing credit risk analysis, implicitly consider the tradeoffs between the conflicting criteria, according to their global preference system. In this way, they conclude on an appropriate aggregation of the partial evaluations of firms on each one of the evaluation criteria, and derive the optimal decision. This complexity of the credit assessment process has necessitated the construction of credit risk assessment models.

Lane (1972) alluded to the fact that the sorting approach to credit assessibility can be used by financial and credit analysts both as evaluation systems of new individual and firms seeking financing as well as screening tools of the firms application and portfolio models which are included in the loan portfolio of a bank or a credit institution.

Credit risk evaluation (Altman and Saunders 1998) is a very important subject as it is a difficult task to predict default probabilities and deduce risk classification. It becomes more and more important for firms to operate successfully and for banks to decide if the loan can be given to the customer or if the credit request has to be rejected.

Basel II standard defines strict restrictions and auditing rules for credit risk evaluation process, thus banking activities are deeply impacted by proper risk system implementation. It is crucial to identify over some successive time periods and select the correct principle or model for credit assessibility and bankruptcy prediction as well as to decide which data and which factors are important .Credit assessment and credit scoring models have been described in diverse ways .

Chijoriga (2011) describes a scoring model as, any empirically derived and statistically sound valuation device for estimating the likelihood that a customer will not pay his obligations when due. Lee and Zhang (2003) also define a credit scoring model as a statistical model that uses

empirical data to predict the creditworthiness of credit applicants. In detail, it means calculating the likelihood that a borrower will repay a loan as promised on the basis of a number of quantifiable borrower characteristics through the application of statistical or operational research methods (Dinh and Kleimeier 2007,; Yap et al., 2011), From these expressions, it is evident that the objective of credit assessment models is to assign credit applicants to either a ‘good credit risk’ group or a ‘bad credit risk’ group (West, 2000; Lee et al., 2002; Yap et al., 2001) and also to clearly provide timely warning to banks on the vulnerability of a borrower (Hua et al., 2007; Li et al., 2011; Rafiei et al., 2011).

In arriving at these scoring models thereof, scholars have relied on a number of statistical methods. Some of these techniques include; multiple discriminant analysis (MDA) (Altman, 1968), probit (Zmijewski, 1984) logit (Ohison, 1980), and artificial neural networks (Wu and Wang, 2000). In the mix of these predictive model developments, the Altman 1968 Z-score model has been popularised and commercialised as a credit assessment model being used mostly in advanced countries. However, commercially available models generally use data from listed firms, which imposes serious constraints on the generalizability of the results to the specific context of privately held firms (Huyen et al., 2007). As a remedy, researchers are now making use of bank specific data and a combination of other techniques to build scoring models (see e.g. Lin, 2009; Chijoriga, 2011) and banking institution in themselves are investing in such internal models as they deliver a well-defined information set at less expense to the bank, and permit them to make faster decisions on loan applications (De-Young et al., 2008).

Deeper into internal bank credit risk management, the Bank for International Settlements (Basel II accord) has encouraged the use of internal rating based tools for curtailing internal risk. In some cases also, it is a regulatory requirement for banks to apply internal risk modeling procedures, which have placed enough responsibility on banks to lookout for new and subjective means of assessing, measuring, and managing their credit risk other than the use of the traditional 5C's which are character, capital, collateral, capacity and condition (Yap et al., 2011). As it stands, traditional financial ratio analysis does not allow for an objective gathering of independent variable evaluations into a single performance score for credit evaluation by credit officers (Emer et al., 2003). Following the Basel II admonition, considerable investments have been made into the development of internal risk models for credit risk assessment by some banks (Fatemi and Fooladi, 2006; Odeh et al., 2010).

Further, considering the economic and financial implications of the 2007-2009 credit crunch, the importance of credit risk management in the banking industry as well as the application of internal and contemporary credit risk assessment tools to aid in the credit granting decision, it has become eminent in the face of the number of risk exposures. Some of these risks include: credit risk, liquidity risk, foreign exchange risk market risk, and interest rate risk among others which may threaten a bank's survival and success (Al-Tamimi and Al-Mazrooei, 2007). Among these risks, credit and liquidity risk exposures are the main causes of bank distress (Greuning and Bratanovic, 2003; Bluhm et al., 2003). However, according to Chijoriga (2011), the severity of credit risk appears to surpass the other risks as far as bank failure is concerned. In this present age, and the seemingly difficulty in predicting the financial environment, it is not sufficient to understand just the primary risks associated with a product or service but also, a subject or

operational requirement for banks to constantly monitor and review their approach to credit and advances which is most often than not, the main earning instrument in their balance sheet (BoG Financial Stability Report, 2011, pp.5).

Bank loans are seen to be an alternative source of business finance, especially for small and medium size enterprises (SMEs) (Jacobson et al., 2006) in the form of start-up capital, working capital or both. These loans in return, constitute a large proportion of risk to banks as it forms part of the core business (Koch and MacDonald, 2000). In Ghana, firms, notably SMEs generally raise concerns about the difficulty in accessing credit from the banks. The banks on the other hand, paint a different picture as they link the situation to the behaviour of borrowers (moral hazards) and their associated high credit risks. With the enactment of the Ghana Credit reporting Act. 2007 (Act 726), it is anticipated that these concerns between borrows and lenders will be reduced if not resolved. The Act (Act 726) allows for the establishment of both public and private companies (called credit bureaus/external credit rating agencies) that would keep information on borrowers for the purpose of assessing their creditworthiness.

Nonetheless, given the asymmetric information that exists between lenders and borrowers, it is imperative for lenders who bear the ultimate risk to have a “personal” mechanism to ensure that they do not only evaluate default risk that is unknown to the ex-ante in order to avoid adverse selection, but also the one that can evolve ex-post in order to avoid moral hazards (Richard et al., 2008). One of the key mechanisms as already noted, is the submission by the Basel II Framework for banks to have Internal Rating Based (IRB) models as one of the ways of managing the credit risk that they are exposed to and means of minimum regulatory capital calculation (BCBS, 2006).

This is one important nature of model analysis as a means of managing credit risk through proper risk modelling and also as a more systematic way for banks to measure changes in the riskiness of their portfolio (Freguson, 2001)

Usually, credit scoring is applied to rank credit information and to target collection activities including the applicant's application form details and the information held by a credit reference agency on the applicant. Besides, the evaluation performance can be improved by using credit scoring which streamlines the process and allows the credit professional to focus only on unusual accounts. Credit assessment can give the credit professional an exposure perspective, mitigate the risk flexibility, and reduce the cost of credit analysis. As a result, accounts with high probability of default can be monitored and necessary actions can be taken in order to prevent the account from being default. Statistically-based credit scoring models, such as linear probability model, discriminant analysis models can be applied to determine the factors that contribute to credit risk (Gordy, 1998)

Over the past decade Bethesda (2004) found out that, the servicing of monetized assets has been reconfigured to create a more efficient credit process and loan market through the application of new technologies, new financial products, and new market participants. Unlike traditional commercial lending, which at one time was predicated on long-term relationships, today's emphasis is on short-term value-added customer relationships. This concept of "value-added" has also brought new meaning to commercial lending as customer relationships are defined as either profitable or not profitable. If they are profitable, this must be evidenced by returns that are

commensurate with the overall portfolio objectives and for the financial institution's return on capital.

1.2 STATEMENT OF THE PROBLEM

With the recent dramatic growth in consumer credit. Accessibility of credit has become one of the main challenges to lending institutions. Credit risk is the risk of financial loss due to the applicants' failure to pay the credit back. Financial institutions and banks are trying to deal with the risk associated with the accessibility of credit, by determining capital requirements according to the risk of applicants and by minimizing the default risk with the use of statistical techniques to classify the applicants into "good" and "bad" risk classes.

By taking into account these facts Basel Committee on Banking Supervision put forward to use risk based approaches to allocate and charge capital. According to the Committee credit institutions the banks have the opportunity to use standard or Internal Rating Based (IRB) approach when calculating the minimum capital requirements

The standard approach is based on the ratings of external rating agencies such as Standard and Poors and Moody's whereas Internal Rating Base is based on institutions' own estimates. Internal Rating Based system can be defined as a process of assessing creditworthiness of applicants. This requires first the determination of the probability of default of the applicant by means of statistical and machine learning credit scoring methods such as Discriminant analysis, logistic regression, probit regression, non-parametric and semi-parametric regression, decision

trees, linear programming, neural networks and genetic programming. The results of credit scoring techniques can be used to decide whether an applicant qualifies. (Altman, 1968)

Furthermore in Ghana, loan applicants often wait for days, or even months for loan approvals. This is because credit assessment decision and the default probability estimation have been the most challenging issues in credit risk assessment. Before the development of mathematical and statistical models Credit analysts use their own judgments in evaluating applicants. These judgments are often poorly made due to lack of symmetric information gap between lenders and borrowers. The decisions may change from one person to another, so they are not replicable and difficult to teach. They are unable to handle large number of applications. But the use of statistical models took the place of judgmental methods (Beaver, 2001).

Credit Risk Assessment assists organizations, such as commercial banks and credit card companies to determine whether or not to grant credit to consumers, on the basis of a set of predefined criteria (Tawakoni, 2003). Credit scoring tasks can be divided into two distinct types: the first type is application scoring, where the task is to classify credit applicants into “good” and “bad” risk groups. The data used for modeling generally consists of financial information and demographic information about the loan applicant. In contrast, the second type of task deals with existing customers and along with other information. Payment history information is also used here. This is distinguished from the first type because this takes into account the customer’s payment pattern on the loan and the task is called behavioral scoring (Atiya, (2005).

Recently, under Basel II committee's recommendations, it is increasingly becoming almost a regulatory requirement for the banks to use sophisticated credit scoring models for enhancing the efficiency of capital allocation. Usually, a credit score is a number that quantifies the creditworthiness of a person, based on a quantitative analysis of credit history and other criteria; it describes the extent to which the borrower is likely to pay his or her bills/debt. A credit score is primarily based on credit reports and information received from some major credit reporting agencies. Using credit scores, banks and credit card companies evaluate the potential risk involved in lending money, in order to minimize bad debts. Lenders can also use credit scores to determine who qualifies for what amount of loan and at what interest rate. The generic approach of credit scoring is to apply a quantitative method on some data of previous customers, both faithful and delinquent customers, in order to find a relationship between the credit scores and a set of evaluation criteria. One important ingredient to accomplish this goal is to seek a good model so as to evaluate new applicants or existing customers as good or bad. In this regard the study seeks to build a statistical model to assess the creditworthiness of new credit seeking firms or clients by using historical financial statements of some private enterprises that have already sourced credit from a commercial bank in Ghana.

1.3 Objective of the study

The main objective of this study was to fit a model that can be used to decide whether or not to grant credit to client by assessing their default risk, help reduce credit granting processing time and simultaneously bringing greater accuracy and fairness to each applicant. This mainly involves:

- Finding out the financial ratios that offer the most predictive significant in determining credit worthiness of firms,
- Building a logistic and Probit regression models and;
- Comparing and evaluating the predictive powers of both logistic and probit regression model in terms of how they work
- Give recommendation to researchers and lending institutions

1.4 Rationale for the study

Logistic and Probit regression models are important tools in statistics and finance or lending institutions. Indeed the absence of a trusted model to help evaluate credit worthiness of clients in an economy such as Ghana's has led to frustrations of the parties involved in credit assessment. The study which involves building logistic and probit regression models and evaluating their predictive powers in terms of how they work will help to determine the probability of default which is a core ingredient of the client's repayment evaluation and will lead to an accurate and a faster evaluation of the client's ability to pay back credit. Applications of these models are expected to enhance decisions on clients applying for credit, the cost of processing of credit and reduction in the amount of risks of default.

1.5 Scope and Limitations of the Study

This research was conducted in the Ghanaian context using data of firms who had sourced credit from one specific bank. This therefore imposes constraints on the generalizability of the models to a different bank since banks have unique internal characteristics and different borrowing

mechanisms. Secondly, the sample includes firms from different sectors of the economy. This will therefore not give the model user the opportunity to associate the model to one particular sector. In effect, it limits the reflection of the exact distinct differences in these firms.

1.6 Organisation of the study

The study is organised as follows: Chapter one covers a general introduction to the study including aspects such as the background to the study, statement of the problem, objective of the study, rationale for the study, scope and limitation of the study and organisation of the study. Chapter Two is devoted to consider the relevant advances made on the credit assessment, and review of related works that have been carried out by other researchers on the topic area (both theoretical and empirical) to the study while Chapter Three explores the methodological framework in dichotomous dependent regression analysis used in building the model. Chapter four focuses and discusses the application of the methodology discussed in chapter three to build the models and how they can be used to help predict the probability of default. Chapter five deals with the summary, conclusions and recommendations and suggestions for future research in the subject area.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter considers the relevant advances made on the credit assessment, and review of related works that have been carried out by other researchers on the topic area (both theoretical and empirical) on credit scoring with regards to the techniques used as well as the predictors. The chapter begins with concepts of credit assessment, the definition of default followed by some theoretical issues on the performance of probit and logit models. Here, classification measures are thoroughly discussed as well as the major distinctions between the two models (probit and logit). On the empirical front, several papers on the credit scoring issues are reviewed in relation to the financial ratios that significantly predict default of firms as well as the techniques that best classifiers' credit applicants.

2.1 THEORETICAL LITERATURE

This section of the literature review focuses on the concept of credit assessment and credit risk management, sources of credit risk, definition of default, the modern and traditional credit processes, perspectives on the performance of probit and logit Models as well as some relationships and variances and the assessability of their performances.

2.1.1 CONCEPT OF CREDIT ASSESSMENT

Credit assessment has been a great concern to lending institutions worldwide. Regulators, banks and bondholders, pension, fund trustees and other fiduciary agents have increasingly used ratings-based criteria to constrain behaviour. The importance of ratings-based regulations have

traditionally been particularly visible in some few countries where it can be traced back to the 1930s.

Fernando Gonzalez et al.(2004) attested to the fact that, with the fast growth of the credit industry all over the world and portfolio management of huge loans, credit scoring is regarded as a one the most important techniques in banks, and has become a very critical tool during recent decades. Credit scoring models are widely used by financial institutions, especially banks, to assign credit to good applicants and to differentiate between good and bad credit. Using credit scoring can reduce the cost of the credit process and the expected risk associated with a bad loan, enhancing the credit decision, and saving time and effort (Lee et al, 2002).

Decision-making involving accepting or rejecting a client's credit can be supported by judgmental techniques and or credit scoring models. The judgmental techniques rely on the knowledge and both the past and present experiences of credit analysts whose evaluation of clients includes their ability to repay credit, guarantees and client's character (Sarlija, et al., 2004). Due to the rapid increase in fund-size invested through credit granted, and the need for quantifying credit risk, financial institutions including banks have started to apply credit assessment models. A credit scoring system should be able to classify customers as good credit those who are expected to repay on time and as bad credit those who are expected to fail. Credit scoring, which helps to classify groups of customers correctly, can also assist banks in increasing sales of additional products. One of the main goals of credit scoring in financial credit institutions and banks is to help the development of the credit management process and to provide credit analysts and decision-makers with an efficient and effective credit tool to help to determine

strengths, weaknesses, opportunities and threats (SWOT); and to help to evaluate credit more precisely. A major problem for banks is how to determine the bad credit, because bad credit may cause serious problems in the future. This leads to loss in bank capital, lower bank revenues and subsequently increases bank losses, which can lead to insolvency or bankruptcy. In developed countries, credit scoring is well established and the number of applications is increasing, because of excellent facilities and vast information being widely available, whilst in less developed or developing countries, less information and facilities are available. Advanced technologies, such as those used with credit scoring have helped credit analysts in different financial institutions to evaluate and subsequently assess the vast number of credit applications. In the findings of West (2000) on the importance of credit, has stated that credit scoring is widely used by the “financial industry”, mainly to improve the credit collection process and analysis, including a reduction in credit analysts’ cost; faster credit decision-making; and monitoring of existing customers. Also, around 97% of banks are using credit scoring for credit card applications, and around 82% of banks (and it was not clear from the original source whether the author was referring to US banks only) are using credit scoring to decide correctly who should be approved for credit card applications. Furthermore, credit institutions and especially mortgage organizations are developing new credit scoring models to support credit decisions to avoid large losses. These losses were considerable. For example, West (2000) reported that 'in 1991 \$1 billion of Chemical Bank's \$6.7 billion in real estate loans were delinquent. Gathering information is a critical issue in building a credit scoring model. In general, through loan application forms, customer bank accounts, related sectors, customer credit history, other financial institutions and banks, market sector analysis and through government institutions, banks may gain competitive advantages by building a robust credit scoring models. By collecting and isolating all relevant information,

credit analysts or “banks” should be able to decide whether a particular variable should be included in the final model or not, and additionally whether a variable fits the real field requirements.

2.1.2. CONCEPTS OF CREDIT RISK MANAGEMENT

Risk is the probability of an event inimical to an entity. It can be positive or negative depending on the event or the circumstance under which risk was taken. In this study, focus was given to risk associated with credit scoring.

There are probable risks faced by lending and financial institutions. Some of which are interest rate risk (the possibility of a reduction in the value of a security resulting in a rise in interest rate), mortgage risk (the possibility that a borrower in a mortgage agreement will fail to make timely principal and interest payments in accordance with the terms of the mortgage), currency risk (a risk that arises from a change in price of one currency against another), liquidity risk (a risk that arises from the difficulty of selling an asset), credit risk, etc. Amongst the various forms of risk, exposure to credit risk continue to be the leading source of major problems faced by financial and other lending institutions. It is the risk most likely to accelerate an institution’s failure. Hence, it is the risk most supervisors of lending and financial institutions would not fail to pay the closest attention.

Whereas credit is the benefit enjoyed by a borrower intended to be repaid at a later date, credit risk is the likelihood that a borrower will fail to pay back credit in a speculated period of time.

Increasingly, lending and other financial institutions are faced with other forms of credit risk apart from the usual loans. These include interbank transactions, foreign exchange transactions, trade financing, bonds, extension of commitments and guarantees etc.

Considering the little confidence lately in credit market, it makes a lot of meaning to employ a better credit risk management practices to minimize exposure to credit risk.

Credit risk management identifies, measures, monitors and reports potential credit risk exposures in an institution. It also ensures that there are adequate funds against unexpected losses as proposed by the Basel Committee, an institution created by the central bank Governors of a group of ten nations. The Basel Committee has issued a document on this proposal to encourage banking supervisors globally to promote sound practices with regards to managing risk. The recommendation on banking laws and regulations issued by the Basel Committee on banking supervision is what we call Basel II. In practice, Basel II attempts to achieve this by putting in place stringent risk and capital management requirements to guarantee that banks and other lending institutions reserve capital suitable enough to protect the institution against credit risk exposure.

According to Basel II, financial institutions should assess the credit exposure for each applicant applying for credit and for each credit facility using the following criteria:

- Probability of Default (PD): It is the probability that an applicant will default within the next 12 months.
- Loss given Default (LGD): It is the amount of capital a financial or lending institution loses when a client defaults. Calculation of the loss given default is done by comparing actual total losses to the total potential exposure at the time of default.

- Exposure at Default (EAD): It is a total value that a financial or lending institution is exposed to at the time of default. Each exposure is given an EAD value and is identified within the bank's internal system. Exposure at default along with loss given default (LGD) and probability of default (PD) is used to calculate the credit risk capital of financial institutions. The expected loss as a result of a client's default is usually measured over a year. The calculation of EAD is done by multiplying each credit obligation by an appropriate percentage. Each percentage used coincides with the specifics of each respective credit obligation.

According to Mehta (1970).The minimum capital requirements (MCR) is given as ,

$$MCR = EAD * LGD * PD - b * EL \quad (2.1)$$

where the expected loss (EL) is

$$EL = PD * EAD * LGD \quad (2.2)$$

and b is the proportion of the expected loss of loan covered by minimum capital requirement

Once these components PD, LGD and EAD are obtained, calculation of the minimum capital requirement is simple as in equation (2.1). The main issues faced by financial and lending institutions are: the necessary information needed to evaluate the components PD, LGD and EAD for each applicant, and the execution of a risk rating system to correctly build a statistically valid and viable model.

2.1.3 Sources of Credit Risk

According to (Bierman and Hausman 1970) there are two main sources of credit risk factors. These are external and internal risk factors. The external risk factors are discussed below as follows:

- **Economic Conditions**

Change in national income and unemployment will have impact on credit risk through change in business cycle, exchange rate, interest rate, credit availability and credit quality. Liquidity crunch or financial problems has the ability to impact borrowers' ability to fulfill their obligation. In addition legal and regulatory change could cause financial institutions to change how they oversee a transaction, as well as the quality and ability of debt collection.

- **Competition**

Competition among financial institutions in terms of growth, profitability and the desire to be a market leader have the ability to cause financial institutions to lower their standards or improperly price their loan products. This could result in higher cost of increasing non-performing loans.

2.1.4 The internal risk factors of credit risk include;

- Underwriting standards

This is a process to determine what type of, to whom, for what purpose and when credit should be granted. Proper credit approval process should comprise proper guidelines on both form and methodology in evaluating borrowers' credit worthiness, setting up of credit line and interest rate appropriate to borrowers' risk and credits. Lenient credit underwriting can incur losses to financial institutions especially when debt repayment cannot be demanded or collateral cannot be seized in time. Many credit risks arise from deficiency in underwriting standards and credit monitoring.

- Inappropriate assessment of credit quality

This problem may result from competitive pressure and credit growth as they tend to put a time constraint on getting accurate data. Moreover, rapid growth and/or entry into new markets can tempt the management to lend without sufficient financial and economic analysis. To facilitate quicker decision making, management may support credit decisions by using simple indicators of credit quality, such as borrowers' characteristics, current and expected value of collateral or support of a parent company or affiliated companies. With rapid credit growth and heightened competition, financial institutions are pressured to introduce new products and services to the market without proper testing. Not in line with the principle of proper credit underwriting, such practice can lead to several financial institutions to serious problems. Financial institutions that

practice proper credit underwriting usually test new products and services before introducing to the general customers.

2.1.5 Definition of Credit

Credit is the trust which allows one party to provide resources to another party where that second party does not reimburse the first party immediately thereby generating a debt, but instead arranges either to repay or return those resources (or other material of equal value) at a later date (Sullivan et al., 2003). The resources provided may either be financial (e.g. granting of loans), or they may consist of goods or services (e.g. consumer credit). Therefore credit encompasses any form of deferred payment which is extended by a creditor, also known as the lender, to a debtor also known as a borrower.

Credit is advanced to beneficiaries who promise to pay in a future date. Individuals, enterprises and other corporate entities have different reasons for accessing credit.

Therefore the purpose and the nature of credit have been categorized into short term, medium term and long term loans. Briefly, short term loans are advances (e.g. personal loans) extended with a repayment period of not more than five (5) years. Medium term loans (designed for Small and Medium Enterprises) have a repayment period that falls between five (5) and ten (10) years. Long term loans (for giant corporate entities) as the name implies have a repayment period of more than ten (10) years. In Ghana most of the credit accessed fall within the short and the medium term.

Advancing credit is key to banks operations, weighing significantly within the asset balance file. It has the potential of generating huge profit, but equally high risk. Practice show that credit risks are the highest registered in time by banks, in connection with losses.

Credit risk is an investor's risk of loss arising from a borrower who does not make payment as promised (Bluhn, et.al. 2002).

2.1.6 The Credit Process

Oldfield and Santomero (1997) investigated risk management in financial institutions. In this study, they suggested four steps for active risk management techniques:

- The establishment of standards and reports;
- The imposition of position limits and rules (i.e. contemporary exposures, credit limits and position concentration);
- The creation of self-investment guidelines and strategies; and
- The alignment of incentive contracts and compensation (performance-based compensation contracts).

Loans that constitute a large proportion of the assets in most banks' portfolios are relatively illiquid and exhibit the highest credit risk (Koch and MacDonald, 2000). The theory of asymmetric information argues that it may be impossible to distinguish good borrowers from bad

borrowers (Auronen, 2003), which may result in adverse selection and moral hazards problems. Adverse selection and moral hazards have led to substantial accumulation of non-performing accounts in banks (Bester, 1994; Bofondi and Gobbi, 2003). The very existence of banks is often interpreted in terms of its superior ability to overcome three basic problems of information asymmetry, namely *ex ante*, *interim* and *ex post* (Uyemura and Deventer, 1993). The management of credit risk in banking industry follows the process of risk identification, measurement, assessment, monitoring and control. It involves identification of potential risk factors, estimate their consequences, monitor activities exposed to the identified risk factors and put in place control measures to prevent or reduce the undesirable effects. This process is applied within the strategic and operational framework of the bank.

Banks must have a process to analyze beneficiaries' ability to service a facility advanced to them. In some instances, stringent policies must be put in place to prevent individuals that involve in fraudulent activities or crimes from accessing a facility. This can be achieved through a number of ways for example using reliable source of references, accessing credit bureaus, or becoming familiar with individuals responsible for managing a company and checking their references and financial conditions. Banks should desist from advancing credit to reputable borrowers simply because they are known to the institution. Each loan application document should carefully be analyzed by a competent credit officer with the appropriate expertise commensurate with the size and complexity of the transaction. Therefore there should be a policy to specify the type of information and documentation necessary for a new credit approval, credit renewals, and/ or change in terms and conditions of previously approved credits. The process of advancing credit is associated with many risks that financial institutions have to deal with.

2.1.7 THE TRADITIONAL CREDIT PROCESS

Joetta (2007) asserted that, under the classical or traditional credit process, the concept of credit risk management had always been to ensure that adequate capital was available for loan funding and that reserves were provisioned according to the borrower's credit assessment. Credit extensions had always used a static approach whereby subsequent to the loan origination, the credit risk of the borrower would remain on the issuing creditor's balance sheet until maturity.

The key elements of this approach usually began with the transaction's origination between the account officer and the borrower. Credit requests were prepared and presented for approval to enter into a transaction that more often than not would be underpriced for the risks relative to the proposed facility terms and structure.

Bethesda (2004) also examined the credit process and pointed out that, the credit granting and subsequent monitoring process was oftentimes accompanied by unpredictable financial indicators that had been derived from limited financial analysis and due diligence.

Loan syndications played an active role in the credit markets at the time however, the emphasis by most lenders was foremost on mitigating credit risks through risk disaggregation rather than managing loan funding for liquidity purposes. In other words pricing was not analyzed to separately identify all of the cost components that lenders incurred for the risks of extending credit, so credit specialists were not able to precisely examine the individual variables that influenced price performance. A common problem under this approach was that the lack of risk-sensitive pricing strategies did not always result in sufficient capital being allocated against rising unexpected losses. This became quite evident as the extension of loans declined from being a leading product for lenders to one of a "loss leader," in anticipation that future ancillary business

from borrowers would compensate for the losses on loans. As a result, when defaults did occur, costs were not recovered, which served to further depress credit earnings.

As the credit markets started to change over the years, the rising defaults led to diverging loan costs and firm revenues that spiraled out of control for most banks. An agency conflict started to develop between bank profitability and account officers' performance compensation while funding and administrative costs on defaulted loans were not being recovered. At the same time, the credit markets were also changing as innovative financial products came on stream into the markets, only to reveal the emerging credit quality disparities among borrowers. It was at this point that financial institutions began to examine their traditional credit risk assumptions by challenging their old assumptions, which had been embedded in a static mind-set, and eventually started shifting to a dynamic perspective that has now become the modern credit risk management approach.

2.1.8 THE MODERN CREDIT PROCESS

According to Boyles et al. (1989) financial institutions began to make comparisons between their historically passive approach to loan management and the more active style of portfolio managers that used most of the same skills and techniques for selecting credits. They found that a distinction between these alternative credit providers and traditional commercial lenders was that portfolio and fund managers did not retain nonperforming assets if those assets failed to provide expected portfolio returns. For banks, however, this required greater emphasis to be placed on portfolio management techniques so that single stand-alone credit requests would be extended to now earn a sufficient economic return so as to maximize the expected credit portfolio returns.

Credit Portfolio Management techniques have become an integral part in credit functions for business units throughout banks, beginning with the evaluation of loan originations. Supporting functions, including relationship managers, the credit department, credit administration, and credit portfolio management, all have complementary roles that are driven by several common themes to reduce the banks' cost of capital and to increase aggregate portfolio performance. In general, transactions are originated by relationship managers in conjunction with each supporting credit function so that when new business is developed it will be based on realizing a hurdle rate of return that is also in line with the banks' portfolio concentration limits. When transactions do not yield the required returns or meet the hurdle rates, the facility is deemed undesirable if the aggregate borrower relationship is found to be unprofitable. Whereas the application of concentration limits under the traditional credit approach had been to reduce the amount of exposure to single borrowers, the practice is now extended to reducing concentration limits to credit events and exposure by borrowers, industries, asset classes, and geographical regions. Credit portfolio analysis is also performed on an aggregate level for borrowers, companies, markets, as well as credit products, all of which are ultimately measured against the desired portfolio's return.

As the new vanguards of the credit process, portfolio managers have empowered banks to adopt a defensive risk posture relative to customer relationships. For credit risk exposures that are not value-added or that increasingly outweigh the rewards, lenders will seek to transfer or mitigate them through loan sales, securitizations, or credit derivatives. Transactions are terminated from the lender's portfolio so that they can be quantified, unbundled, and repackaged into newly manufactured credit products for resale to third-party investors. By repackaging corporate credit

risk into new pools and classes of debt that are sold to a broad range of investors, the credit markets have created a new product segment in the syndicated, secondary, and capital loan markets. The expansion and growth of the credit derivative markets by adopting the practices of modern credit risk management, the banking industry has also become resilient in managing the deteriorating credit quality among corporate borrowers.

2.1.9 LOAN

According to Gordy et al., (2000) a loan is a resource, mostly in momentary terms given out to a qualified applicant with an agreement to pay back the money with interest at a specified date. Typically, the money is paid back in regular installments. The loan is provided at a cost, referred to as the interest on the resource received. This provides an incentive for the bank to engage in the loan. There are two major characteristics that vary amongst loans obtained from a banking industry. These are the security required to access the loan and the terms of the loan.

Considering the security required to access the loan, there are two types:

- Secured loans
- Unsecured loans.

- Secured loan

A secured loan is a loan backed by a guarantee of payment for the loan. The borrower by law gives up ownership of collateral used as security to the lender. A typical example of a secured loan is a mortgage loan. This is used by clients in purchasing properties. A mortgage loan is

procured by a buyer to pay off the seller of a piece of property in full. The buyer then owes the mortgage lender the total amount borrowed with interest and fees. As collateral the lender of the mortgage keeps ownership of the said property until the buyer pays the mortgage off in full. However, the buyer occupies the property as if it were already his or her own. If the borrower defaults on the mortgage loan, the bank has the legal right to sell the property to get back the money that has been lost. Another form of a secured loan is a car loan. Just as a mortgage loan is secured by housing, a car loan may be secured by the car. There are two types of auto loans. These are direct and indirect auto loans. For a direct auto loan, the bank gives the loan directly to the client. In the case of an indirect auto loan, the car dealership acts as an intermediary between the bank or financial institution and the client.

- Unsecured loans

These are monetary loans not backed by any guarantee. Some of these include credit cards loans, personal loans, bank overdrafts, corporate bonds etc. (Modigliani and Miller 1998).

2.1.10 Definition of default

Historically, credit risk models were developed using the default criterion bankruptcy(Mavri,etal2008).However considering the typical operations of financial institutions and the road maps to eventual bankruptcy the banks will incur losses before the firms/s they had borrowed to even go bankrupt. Thus, by necessity, they make loan-loss provisions for such debts which eventually affect and erode their profitability. By the nature of bankruptcy, it is usually triggered by the default on debt servicing (Lennox, 1999) hence the two circumstances (default and bankruptcy) must not be mixed. Additionally, there is a legal implication to bankruptcy which varies from

country to country and moreover, firms, experiencing financial distress may not automatically face legal failure or go bankrupt (Bhimani et al., 2010). Bankruptcy occurs when a company is declared insolvent and the assets liquidated in order to repay its creditors (Bhimani et al., 2010). On the other hand, default is described as the failure of a company to make timely payments of interest or principal to lenders. Furthermore, default occurs prior to bankruptcy and the former may not lead to the latter (Grammenos et al., 2008). As Barnes (1990) reiterates, the relevance of making the difference between bankruptcy and default is crucial given that failure to meet financial obligations does not necessarily lead to bankruptcy.

Presently, several expressions such as distress and failure are applied to mean 'default'. Beaver (1966) defines failure as the inability of a firm to pay its financial obligations as they mature. Due to these developments as to what distress, failure and bankruptcy are, studies carefully use the terms 'failure and/or distress' to mean default barring any legal considerations with strict stances (see Lin, 2009, Laitinen, 2010; Chijoriga, 2011). The focus of this study is predicting default risk of firms but not bankruptcy and so it is important to describe what default actually means in this research context. The importance of defining financial failure is emphasised by Altman (1984). In Altman's opinion, failure is independent of its outcome. This calls for the definition of our dependent variable (default) in consistence with an ex-ante approach and for a financially based definition of distress that is independent of its legal consequences (Pindado et al., 2008).

In the Basel Committee on Banking Supervisions' (BCBS) 2004 capital adequacy framework, the committee announced an internal ratings-based approach (IRB) which could form the basis for setting capital charges for banks with respect to credit risk (BCBS, 2004). The framework in

general defines default as any credit loss event associated with any obligation of the obligor, including distressed restructuring involving the forgiveness or postponement of principal, interest, or fees and delay in payment of the obligor of more than 90 days. The revised version of the accord, Basel II framework (BCBS, 2006) exclusively outlines the following reference definition of default; “a default is considered to have occurred with regard to a particular obligor when one or more of the following events have taken place”. “The bank considers that the obligor is unlikely to pay its credit obligations (principal, interest, or fees) to the bank in full without recourse by the bank to actions such as realizing security (if held)”.

“The obligor is past due more than 90 days on any material credit obligation to the bank”

From our discussions so far, it is apparent that researchers and practitioners interchangeably use terminologies such as distress or failure to also mean financial default by clearly defining it and stating their stance. With the ensuring definition of default, this study adopts the definition of default that is independent of any legal implications (e.g. Beaver, 1966; BCBS, 2004; BCBS, 2006). Consequently, this present study uses a financial criterion in defining default, which is the inability or failure of a firm to fulfil its agreed upon financial obligations when due. This will facilitate the prediction of the probability of default of firms seeking credit. As such, distress and failed firms are considered as those that have defaulted on their financial obligations when they were due.

2.1.11 Theoretical Perspectives on the Performance of Probit and Logit Models

Logit and probit models are two regression methods categorised under Generalized Linear Models (GLM) which can be used when the dependent variable in the analysis is categorical in nature' (Shariff et al., 2009). In other words, they are techniques for estimating the effects of a set of independent variables on a binary (or dichotomous) dependent variable (Berry, 2005). Logit model is used to forecast probability of an event by fitting data (represented by some variables) to the logistic curve (Li et al., 2011). In this research, the probability of an event happening is default, denoted by 1 (one) if the event occurred (firm defaulted) and 0 (zero) if otherwise. The purpose of logistic modelling (and also probit) as in other modelling techniques, is to find a model that best fits the data and is also the simplest, yet, physically practical and resolute in describing the relationship between the dependents and the explanatory variable (Hosmer and Lemeshow, 1989).

Opinions regarding the selection of probit or logit as binary response mode is mix since the two approaches basically appear to yield similar results. As it stands, there is little to differentiate between the models which party fits the question posed by Gujarati (2004) that "between logit and probit, which model is preferable"? Nonetheless, according to Hahn and Soyer (2007) this affirmation only seem to be true for univariate binary response models and therefore, for multivariate binary responses models, such opinion is misleading because model fit can be improved by the selection of the appropriate link function. Hahn and Soyer (2007) further postulates that, if the researcher is interested in both in-sample and out-of-sample predicted ability, then the probit model is clearly preferable. It is however asserted in some quarters that the logit model outperforms the probit model in terms of predictive accuracy on the field (Altman and Sabato, 2007).

One major statistical multivariate assumption concerning dependence techniques is normality (Hair et al., 2006). Under this assumption, Finney (1952) suggest using the logit over the probit transformation if data is not normally distributed since the logit model will provide a better prediction accuracy owing to the distributional nature of the probit model (follows a normal distribution). Similarly, Shariff et al. (2009) argues that, a regression of the logit seems to be the most robust approach as against probit if normality of data is in doubt. This therefore means that logit estimations are expected to give better prediction accuracy and results as compared to probit when the data used does not meet the multivariate normality assumptions. In addition, Hahn and Soyer (2007) put forward that in multivariate probability models, logit provides a better fit than probit in the presence of extreme independent variable levels while on the contrary, probit offer a better fit where moderate data set (size) is available.

2.1.12 Performance Criteria of Prediction Model

There are many statistical measures of model performance. That is, the ability of a risk model to rank or predict risk of a binary outcome (Beling et al., 2005). Traditionally in logit and probit model, fit, the “pseudo R^2 ” coefficient has mainly been relied on and served as a goodness-of-fit and performance measure. However according to Berry (2005), reliance on such statistics have not achieve wide acceptance as a standard measure of performance as compared to percentage correctly predicted (PCP) or percentage correctly classified (PCC).

Much of the theoretical literature on the performance of prediction models is based on the evaluation of the hold-out/validation/out-of-sample predictions normally shown by the PCP or PCC (Diebold and Mariano, 1995; McCracken, 2000; Thomas et al., 2005). The percentage correctly classified or predicted, measures the proportion of correctly classified cases in a sample of estimation data (Baseness et al., 2003). Nevertheless, selection of a model based on its out-of-sample prediction as a result of the in-sample performance is also optimal (Donkers and Melenberg, 2002). In principle, a good prediction model should predict (perform) well both in-sample and out-of-sample,. Therefore a test for predictive performance should result in similar conclusions for the estimation and the valuation sample (Donkers and Melenberg 2002). Since predictive accuracy is one of the most important indicators of model effectiveness, it is imperative to compare models and settle on the one that is most accurate since a unit difference can be crucial when applying the model to default risk (Li et al., 2011).

Notwithstanding the importance of PCC as a performance measure, Baesens et al. (2003) asserted that in several instances, the PCC may be an inadequate performance criterion in view of the fact that it assumes equal misclassification costs for type I error and II error predictions which is problematic since for most real life problems, one type of classification error may be much more expensive than the other. By implication, better methods of comparing scoring models would be useful (Thomas et al., 2005). A superior performance measure which is noteworthy is the receiver operating characteristic (ROC) curve (Beling et al., 2005). The ROC has mostly been employed in studies to ascertain and compare the performance of scoring models by examining the area under the ROC curve (AUC) (Verstraeten and Poel, 2005).

The ROC curve is a two-dimensional graphical illustration of the sensitivity on the Y-axis (highly risky applicants who can be perfectly identified and rejected) versus 1-specificity on the X-axis (good applicants rejected) for various values of the classification threshold that yields and AUC or a plot of the cumulative score distribution of the bad sub-population versus the good sub-population (Beasens et al., 2003; Beling et al., 2005). The AUC provides a simple figure of merit for the performance or efficacy of the constructed classifier and its measurement is closely related to the Gini coefficient which is between 0 percent and 100 percent (Thomas et al., 2002; Thomas et al., 2005) meaning that the higher the value, the better the discriminatory ability of the model.

Simply put, AUC offers an estimate of the probability that a randomly chosen defaulter (positive predicted borrower) is correctly rated (i.e. ranked) higher risk than a randomly selected non-defaulter (negative predicted borrower) (Verstraeten, and Poel, 2005) or where all non-creditworthy firms can be perfectly identified and rejected by scores below a given cutoff value on the line of equality where there is no discrimination power and applicants are selected at random (Beling et al., 2005). In ROC space, the greatest increase in expected loss is loan lines parallel to the vertical axis exist, pointed towards the origin thus where every applicant seem to be accepted but sensitive and the greatest increase in expected profit is loan lines pointed towards the upper-left corner where there is perfect discrimination (Beling et al. 2005).

Talking about threshold or cutoff score for accepting or rejecting loan applicants, if we consider an acquisition policy with a single score or cutoff (v), where only applicants with scores higher than the cutoff are accepted, then each point on the ROC curve yields the fraction of unworthy-credit clients rejected as a function of fraction of the worthy ones rejected (type II error) (Beling et

al., 2005). The cutoff point or value according to Capon (1982) is set by the creditor on the basis of the probabilities of repayment and non-payment associated with the various point scores and the trade-offs between type I and type II errors. The errors arise as a result of misclassification of applicants given the minimum cutoff score for accepting or rejecting credit applicants. A Type I error is identifying borrower as good (because it has a value above the cutoff) but it's an eventual defaulter and a Type II error is identifying a company as bad (because it has a value or score below the cutoff) but in actual fact will not default (Kealhofer, 2005)

According to Kealhofer (2005), three aspects of testing default risk measures deserve special attention. These are: arbitrary metric, error trade-off, and sample dependence.

- **Arbitrary metrics:** Different default risk procedures are not based on the same metric and as such, cutoff scores (v) are unrelated from one metric to another and therefore by comparing different techniques at arbitrary cutoff value is generally meaningless. The author however suggest that the difficulty can be overcome by comparing the Type I error rates of the models for which the cutoffs have been set to produce the same levels of Type II error.
- **Error trade-off:** The levels of Type I and Type II errors are related to each other and to the level of the cutoff (Capon, 1982), Hence, using a very high cutoff minimizes Type I error, but maximizes Type II error. Thus, the higher an acceptance cutoff is set, the lower the type I error (accepting bad applicants), while the lower a rejection cutoff values, the lower the type II error (rejecting good applicants) (Capon, 1982).
- **Sample dependence:** Also, Kealhofer (2005) assert that, the levels of error depend on a particular sample tested and in a broad spectrum; one cannot compare errors from one sample

with errors from another sample. For instance the characteristics of sample A may be distinct from that of sample B. Consequently, the differences will invariably translate into different average default rates and different levels of error.

2.1.13 Similarities and Differences Between Probit and Logit Models

It is difficult to statistically distinguish between logit and probit models, as both models are very similar and rarely lead to different conclusions (Bhimani et al., 2010). In this study we have classified them on the basis of their distribution, coefficients, and nature.

- ***Distribution:*** In many applications involving the probit and logit models, particularly those concerning decision making, the latent dependent variable may represent the probability that an event occurs or the preference level that a decision maker has for two alternative outcomes (Aldrich and Nelson, 1984). On the basis of probability distribution, the probit is assumed to follow the cumulative normal distribution, while in logit, it is assumed to be based on the logistic distribution (Aldrich and Nelson, 1984; Li et al., 2011). In addition, through both models have a mean value of zero (0), their variances are different (Gujarati, 2004). That is to say that logit regression does not require multivariate normal distributed variables or equal dispersion matrices (Ohlson, 1980; Zavgren, 1983). The cumulative distributions of the two models are depicted in Figure 2.1.

- ***Estimated coefficients:*** There is little to distinguish between logit and probit models for the reason that both curves are so similar as to yield essentially identical results (Shariff et al.,

2009). However, applying probit and logit analysis to the same set of data produces coefficient estimates which differ approximately by a factor of proportionality, and that factor should be about 1.81 (Aldrich, and Nelson, 1984). Therefore, if the probit coefficient is multiplied by 1.81, that is $\left(\sim \frac{\pi}{\sqrt{3}} \right)$, you will get approximately the logit coefficient (Aldrich, and Nelson, 1984).

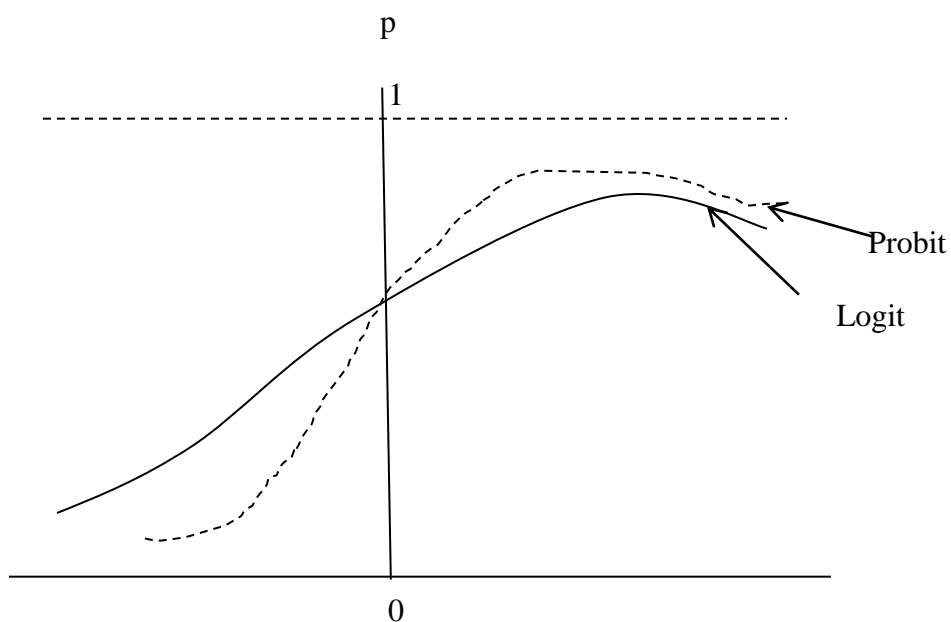
Alternatively, if you multiply a logit coefficient by $0.55 = \frac{1}{1.81}$ you will get the probit coefficient (Gujarati, 2004)

Despite these computations, the estimated parameters of the models are not directly comparable. It is also important to note that in predicting who is likely to repay a loan and who will default, any approximations will probably lead to misclassification of an applicant and hence lead to type I or II errors which in essence will affect the credit granting decision. As such, in risk modeling, one must bear in mind the consequences of such approximations since even an improvement in accuracy of a fraction or a percent might translate into significant future savings for the model user (Beasens et al., 2003).

- **Nature** : Gujarati (2004) observes that in most applications, the probit and logit models are quite similar. However, the main difference is that, the logistic distribution has slightly fatter tails, which can be seen from figure 2.1. what this means is that, the conditional probability (P_i) approaches zero or one at a slower rate in logit than in probit and as such, there is no compelling reasons to choose one over the other or substitute one model for the other (Gujarati, 2004). In practice nonetheless, many researchers choose the logit model over the probit because of its

comparative mathematical simplicity and the flexibility as far as multivariate normality is concerned (Gujarati, 2004; Hair et al.,

Figure 2.1: Probit and Logit cumulative distributions



Source Gujarati (2004)

2.2 Empirical Review

This aspect of the review delves into the findings of other related studies in terms of the ratios that significantly predict default or distress and also the models that best classifies the sample.

2.2.1 Financial ratios as Predictors of Financial Default

It is well established that the effective use of screening technology greatly reduces the informational asymmetries between borrowers and lenders, thereby enhancing the efficiency of the financial intermediation process (Psillaki et al., 2010). Over the past decades, a vast literature has emerged concerning the development of statistical models.

Designed to predict if firms will either fail or experience some form of financial distress, such as loan default and bankruptcy with the help of financial ratios (Khatwani et al., 2006). In order to build a scoring model, historical data on the performance of previously granted loans and borrower characteristics are required (Yap et al., 2011). Based on these performance indicators notably financial ratios, a good scoring model could give a higher percentage of scores to 'good borrowers' and lower scores to those who are 'bad borrowers' by assessing specific performance indicators (Yap et al., 2011). Despite the skepticism surrounding the use of the ratios as means of assessing creditworthiness, they have become useful and acknowledge in a variety of areas including credit lending (beaver, 1966)

One of the primary issues of credit scoring research has been to determine what variables significantly influence the probability of default (Marshall, 2010) in testing the usefulness of ratios as predictors of failure, Beaver (1966) independently tested a series of ratios including: Cash Flow Ratios, Net-Income Ratios, Debt to Total Asset Ratio, Liquid Assets to Total Asset Ratio. Liquid-Asset to Current Debt Ratio, and Turnover Ratios, After conducting the univariate analysis, the author found cash-flow to total debt ratio to be the strongest in the ability to predict failure while the net-income to total assets ratio predict second bests. In Beaver's paper, the third best ratio to predict failure is the total debt to total assets ratio while the liquid-asset ratio

performed the least. From this study, It can be observed that, financial leverage, profitability, and liquidity are key indicators of the health of a firm and for that matter, serve as good indicators of financial distress. This pioneering work paved way or the development of multivariate predictive models to businesses.

In a follow up study Altman (1968) found five financial ratios as significant predictor variables for bankruptcy in his Z-score model, these consist of: Working capital/Total assets, Retained Earnings/Total assets, Earnings before interest and taxes/Total assets, Market value equity/Book value of total debt, and Sales/Total assets ratios. Amongst these ratios, the author found the profitability ratio to be the highest contributory factor to predict distress. Altman described this outcome as not supervising considering the fact that the incidence of bankruptcy in a firm that is earning profit is almost nil. On the contrary, profitability does not necessarily means cash hence firms making or reporting profit still have a certain chance of failure as in the case of Enron. It is clear from here that firms that suffer cash flow problems are more risky and susceptible to distress. Emel et al. (2003) also found that 'better' firms are those that in general, are less risky, financially efficient, more liquid, and are adequate in terms of capital. .

Based on data from the USA telecom industry, Foreman (2003) demonstrates that traditional financial ratios (profitability, capital structure, and the power to fiancé growth internally) are good enough to tell the probability of a firm's failure. One surprising yet not out of place finding in Foreman's stud is that, the author found a positive but significant relationship between the liquidity measures and probability of failure. It must be noted however that the consequential effects of extensively large holds for the purposes of remaining highly liquid has detrimental cost

as assets will be tied down without being invested. The author also attributed this deviation from the theory or norm to the extraordinarily large working capital holdings and over-expansion of the firms studied.

Whereas the eligibility of financial factors as inputs for internal credit scoring is widely accepted and for that matter not in doubt (Chijoriga, 2011), the role of non-financial factors remains unclear even though in certain quarters, they have proven to be good distress predictors when used together with financial ratios (Zavgren, 1985; Bhimani, et al., 2010). Analysing credit file data from four major German banks with the aid of the probit model, Grunert et al, (2005) found evidence of improved model performance in terms of predictive accuracy of default when both financial and non-financial variable/factors are simultaneously used. The study further showed that financial profitability ratios, liquidity ratios, and leverage ratios are significant indicators of default.

2.2.2 Exploration of more Essential Ratios to Predict Default

Aside the inclusion of long-established financial ratios in predictive models, efforts are being made to discover and increase the amount of variables in such models. Khatwani et al (2006) in constructing a loan default model, factored thirty one (31) financial ratios into their model. However, after careful stepwise logistic regression and multiple discernment analysis, only six significant variables were retained in the model. These are: Return on Assets (ROA) ratio, Current Ratio, Interest Convergence ratio, receivables Turnover ratio, Fixed Assets/Total Assets ratio and Working Capital/Net Sales ratio. This further confirms the importance of firm profitability as a key ingredient for firm survival. This outcome corroborates the Atman (1968) results which found

profitability to be a significant factor in predicting failure as well as leverage and liquidity of the firm. Similar to this, Chijoriga (2011) found ratios such as profitability, Liquidity and leverage to be significant and key in the lending environment to assess the credit risk of a loan applicant.

Altman and Sabato (2007) applied the logistic regression analysis as a credit risk model for SMEs in the USA. The authors manually entered seventeen (17) accounting ratios into the SME risk model. The authors however found five significant ratios in predicting distress. These ranged from profitability ratios, liquidity ratios to leverage ratios. This result indicates that for firms to be able to withstand shocks and be solvent both in the short and long term, they must be profitable and be able to transform assets into cash in order to pay of debts (be liquid). More especially when debts to creditors must be paid with cash and not profit (Appiah and Abor, 2009).

As it stands, the inability of a firm to generate enough cash from its operations may force the firm to borrow more money or to dispose of its capital investments to meet its obligation (Rujoub et al., 1995). Also, it is clear that firms with huge debts are likely to face distress and interest rate risk when earnings fall short of interest expense. At this stage it is important, to talk about one other firm characteristics, size. Chen et al. (2010) found that the asset size of a firm has a significant impact on its credit risk exposure indicating that, the probability of default is biggest among small sized firms and much lower in medium and large-seized ones. The pioneering findings of Ohlson (1980) like other studies identified four basic factors as being statistically significant in affecting the probability of failure with one year. These are: the size of the

company; measure of the financial structure; measure of performance; and measure of current liquidity.

In a Tunisian context, Matoussi and Abdelmoula (2010) found accrual; cash-flow and collateral variables as the best default indicators or predictors. The result reiterates the significance of cash-flow to a business. This can be described as the 'life-blood' of any firm (Rujoub et al., 1995). When this 'blood' ceases to flow, the business 'dies out'. In addition to cash flow, the scholars also found tangible collateral as another significant predictor of default. The eminence of tangible collaterals in their results is not surprising as it gives a reflection of the credit risk assessment criteria in developing countries, where collaterals are still being used as yardsticks for lending. In a similar instance, Affuso (2006) finds that lenders' credit quote is provided by determining the value of collateral of the borrower mainly because of information asymmetry.

To buttress the importance of cash flow ratios to the health of a firm, an earlier study by Rujoub et al. (1995) is a good example. The author extensively used only a wide array of cash flow ratios to predict financial failure. The empirical evidence of the paper revealed high performance of the ratios to predict default. Exclusively, the cash flow predictor variable (data) yielded 86.36 percent and 789.79 percent classification accuracy on in sample basis for one year and two years prior to failure respectively. This finding goes further to support how crucial cash flow is to the existence of a firm. Any seizure of which will lead to the demise of such a firm.

With the aim of providing a two stage early warning model for evaluating credit default risk, Pslillaki et al. (2010), found that apart from the importance of non-financial performance indicators, profitability is a significant ex-ante predictor of firm failure. Similarly, the authors

found that firms with more liquid assets have less of a chance to fail while the effects of leverage and growth opportunities (intangibles), capital-turnover ratio and firm size generally had a significantly negative relation with the likelihood of business failure. Contrary to this outcome, Jacobson and Roszbach (2003) showed that firm size does not affect the default risks associated with a loan.

Bhimani et al. (2010) modelled default risk with an initial 30 accounting ratios and non-accounting information. The study found interest costs to gross income, number of days in payables and receivables to have a positive and significant influence on the probability of default. Other ratios which were found significant but negatively related to default include: financial and asset coverage, the investment ratio, return on equity and investment, solidity, variation in gross incomes, and working capital to total assets ratios. In terms of the non-accounting variables, it was established that age influences default negatively. In view of these findings, the authors re-emphasised the role of non-accounting information on default prediction which together with other influential predictor variables, can serve as early warning signals in policies underlying supervision, and the default probabilities in the assessment of financial pressures in the corporate sector.

Establishing a diagnostic model for business crises prediction, Lin et al. (2011) explored potentially useful but previously unaware financial features for better prediction accuracy. The study identified five useful financial ratios to help predict financial distress. Three of the ratios relate to the company's overall business performance and the other two include tax rate and continuous EPS as measures of firm future development. The performance indicator borders on; profitability (Net income/total assets), liquidity (current ratio), and leverage (cash flow/total

debt). This means that a healthy firm must be the one that is viable in the long term, has good returns, be able to generate enough resources to meet its financial obligations when due (interest coverage). In a related study, Thomas et al. (2011), found that operating efficiency, profitability, solvency and, cash flow variables are essential to provide an early warning signal for corporate performance and creditworthiness. The importance of these ratios has been evident in the findings of earlier reviewed studies (e.g. Beaver, 1966; Altman, 1968; Rujoub et al., 1995; Bhimani, et al., 201; Matoussi and Abdelmoula, 2010)

Pindado et al., (2008) conducted a cross sectional study by using G-7 country data to develop an ex-ante model for estimating financial distress likelihood. The results revealed that profitability and financial expenses are statistically significant in predicting financial distress. Specifically, return on assets ratio (ROA) and retained earnings/total assets as measures of profitability as well as financial expense/total assets as a measure of leverage were found to be the ratios that contribute to the predictive ability of the model. Marshall et al. (2010), studied credit applicants in the United Kingdom with the motivation to reduce explanatory variable dimensions for credit scoring research. Their results produced a statistically significant correlation between loan approval and applicant performance indicators. Up till now, financial ratios have been the main means of determining credit worthiness of credit applicants and for forecasting default/distress (Laitinen, 2010).

From our discourse so far, it is evident that ratios covering a company's profitability, liquidity, leverage levels size and general cash flow activities are necessary and key to the health and worth of a firm. These have dominated the empirical literature as far as the significant predictor

variables in any credit scoring model are concerned with profitability ratios significant in most studies. Appiah and Abor (2009) however have raised concerns on the 'over reliance' on profitability as a measure of failure of firm resilience and solvency asserting further that following the events of this present era, profitability of a firm stand in a limbo given the collapse of bi profit making firms like Enron and WorldCom.

2.2.3 Performance of Financial Distress/Default Prediction Models

In practice, there are numerous statistical methods for building credit scoring or distress models, for the purpose of managing credit risk, commercial banks use these various scoring methodologies to evaluate the financial performance of client firms (Emel et al., 2003). A few of these techniques include: multiple discriminant analysis (Altman, 1968; Chijoriga, 2011), logit (Ohlson, 1980; Foreman, 2003; Lee and Zhang, 2003), probit (Zmijewski, 1984), Artificial Neural Networks (ANN) Wu and Wang, 2000; Lee and Chen, 2005), and at some instances, a combination of all four techniques (Lin, 2009).

In recent times, more quantitatively demanding approaches such as data envelopment analysis (DEA) Psillaki et al., 2010), and case-based reasoning (CBR) (Li and Sun, 2011) are being employed to predict distress, assess credit risk, and support the credit decisions process. These techniques are estimated to improve the in-sample and out-of-sample predictive accuracy rates. Among these techniques, discriminant analysis is the most commonly used statistical credit scoring method, but often criticized due to its strong model assumptions (Lee et al., 2002) Multiple discriminant analysis (MDA) assumes dichotomous data, a specified prior probability of two groups (Balcaen and Ooghe, 2006; Hair et al., 2006)

In reality however, the assumptions may be valid or invalid (Zavgren, 1985) due to the fact that the assumption of multivariate normality is often violated for distress data without effective solutions (Li et al., 2011), Notwithstanding, the multiple discriminant analysis stands as one of the four most used predictive models aside the light, probit, and artificial neural network models (Lin, 2009)

Altman (1968) for the first time applied the MDA approach to predict bankruptcy of sixty six (66), (33 failed and 33 non-failed) United State firms with considerable amount of success. From the paper, the discriminant ratio model proved to be extremely accurate in predicting bankruptcy correctly in 94 percent of the initial sample and with 95 percent of all firms in the bankrupt and non-bankrupt groups assigned to their actual group classification. It was further found that per the model, bankruptcy can be accurately predicted up to two years prior to actual failure with the accuracy diminishing rapidly after the second year. In a similar instance, Chijoriga (2011) observed that predictive power ridicules as the lag year increases.

Substituting the MDA to avoid some fairly well known problems associated with it, Ohlson (1980) applied a conditional logit probability model as a remedy to predict bankruptcy. The empirical results show that the logit has good failure predictive rate of over 90 percent. Despite having prediction rate in the 90 percent region similar to Altman (1968), Ohlson criticised previous studies ,notably the Altman (1968) study because in his view, those papers appear to have overstated the predictive power (in terms of forecasting)of the models developed and tested due to their relatively small error rates. One notable advantage of the logit model over the

multiple discriminant analysis is that it does not necessarily require the strict multivariate normality assumption which are prerequisites for a valid multiple discriminant analysis (Hair et al., 2006). This therefore places the logit model at an advantageous position over the multiple discriminant analysis approach.

As if the logit model was meant to solve the then financial distress prediction problems, Zmijewski (1984) pioneered the use of the probit model by using it to predict distress. In the same way as Ohlson (1980) criticised previous studies, Zmijewski, also criticised the earlier methodologies and studies for sampling bias, earlier methodologies and studies for sampling bias based on choice-based bias. The author split these into two: choice-based bias and sample-selection bias. According to Zmijewski (1984), a choice-based sample bias, results when a researcher first observes the dependent variable and then selects a sample based on that knowledge. Thus, the probability of a firm entering the sample depends on the dependent variable's attributes he also described a sample selection bias to result when only observations with complete data are used to estimate the model and incomplete data observations occur non-randomly. As it is, Zmijewski found that both biases result in asymptotically biased parameters and probability. Despite clear existence of such biases, the author concluded that in general, it does not appear to affect the statistical inferences or overall classification rates when random sampling is assumed. In a related work, Verstraeten and Poel (2005) found the existence of sample bias in their research but recap that, the impact or effect of such bias on credit scoring model performance and profitability is modest despite their presence.

After the way was paved for the three classical statistical models (multiple discriminant analysis, logit, and probit), they have become benchmarks for credit risk modeling and financial distress prediction. Researchers that propose new models often compare predictive performance of those new models with the traditional statistical models (Li and Sun, 2008). Aside the origination of the conventional models, nonparametric statistical approaches have been acclaimed to immensely support the credit decision (Thomas, 2000). Notwithstanding these developments, the traditional models still appear to provide good results as far as predictive accuracy and performance is concerned (Mavri et al., 2008; Lee and Chen, 2005).

2.2.4 Comparing the Predictive Ability of Different Default Prediction Models

Kolari et al. (2002) used both the parametric method of logit analysis and the nonparametric approach of trait recognition to develop classification early warning systems (EWEs) based on original samples and to also test the efficacy of the models based on the prediction accuracy using holdout samples. The study found that both logit and trait recognition performed well in terms of in-sample classification results. However, with regards to holdout sample performance, trait recognition outperformed the logit model in terms of minimizing Type I and II errors. Huang et al. (2006) performed a comparative study between the logit model and the artificial neural network approach. Their empirical evidence indicated that the logit model perform well in terms of predictive accuracy than the one fitted by artificial neural network technique. This is unlike the findings of Kolari et al. (2002) who found a dominance of the nonparametric technique over the parametric approach.

Following the Case-Based Reasoning (CBR) technique with financial ratios derived from financial statements of some Chinese firms. Li and Sun (2008) indicated that the ranking order based case-based reasoning statistically outperforms MDA, and logit significantly in financial distress prediction 1 year prior to distress. In a follow up paper, but this time applying principal component case-based reasoning, Li and Sun (2011) showed that by using more recent based prediction techniques, risk or distress models yield better predictive accuracy rates. The authors again revealed that, the adopted method outperforms the two classical statistical methods of multiple discriminant analysis and logit in terms of predictive ability.

In another comparative study to explore the performance of the back propagation neural networks with discriminant analysis and logit credit scoring models, Lee et al, (2002) found that accuracies increase in terms of the neural networks and hence outperform traditional multiple discriminant and logistic regression approaches. The paper further demonstrated that beside the better credit scoring accuracy of the hybrid method, it also has the lowest Type II error associated with high misclassification costs. In a related comparative study, Lin et al. (2007) used the DEA, neural, network and logistic regression methods to establish a prediction model of financial distress. Here, the DEA proved superior over the logit and neural network in predicting failure correctly.

As mentioned earlier, after the singular emergence of prediction models, many of the later default prediction studies have aimed at drawing comparisons between the available models to ascertain the one that offers the highest predictive performance. Following in this path, Odeh et al. (2010) examined the performance of the ANN, logistic regression and adaptive neuro-fuzzy inference

system in predicting credit default. The empirical findings show that correct credit default predictions (in and out-of-sample) vary with model used. However, the adaptive neuro-fuzzy inference system model had the highest in-sample accuracy in being able to identify defaults (sensitivity) in the portfolio with a measure of 69.87 percent, followed by the artificial neural network (61.51 percent) while the logistic regression model recorded the lowest predictive accuracy (44.42 percent). Notwithstanding, considering out-of-sample performance, the logistic regression model exhibited the best classification accuracy (90.77 percent) followed by the adaptive neuro-fuzzy inference system (51.97 percent) and the ANN exhibited the least out-of-sample performance. Since credit scoring models are applied to samples outside the training sample, choosing a model based on its out-of-sample performance is optimal.

Li et al. (2011) combined the classical models and random subspace binary logit (RSBL) model (or random subspace binary logistic regression analysis) to forecast corporate distress in China. The results indicate that the RSBL performs significantly better than the traditional models (i.e., MDA, logit, and probit models) in predicting corporate failure. However, in terms of the three classical methods, the probit model out-performs its counterparts with the MDA yielding the lowest predictive accuracy. In a similar empirical default prediction exercise, Laitinen (2010) found a relatively higher prediction ability when the logit model was applied; recording an overall accuracy of 73.85 percent for the estimated sample while the hold-out sample correctly verified 74.30 percent of the validation sample. This study re-emphasises the supremacy of the out-of-sample predictive power of the logit model.

Abdullah et al. (2008) employed the MDA and logistic regression to predict corporate failure of listed Malaysian companies. The authors found that when the holdout sample is included in the

analysis, discriminant analysis has the highest accuracy rate over the logit model. As discriminant analysis has the highest accuracy rate over the logit model, as discussed previously (see Kolari et al., 2002; Lin et al., 2007; Odeh et al., 2010) it is clear that statistical models have their strengths and outperform each other under different circumstance. Nonetheless, it appears that regional differences also have a significant impact on the performance of the models. For example, what pertains in African might not be the same for the Asian region or the United State of America and as such, data from these blocks are certain to have distinct characteristics.

Examining the predictive ability of the four most commonly used financial distress prediction models (MDA, probit, logit, and ANN) in Taiwan; Lin (2009) revealed that among these four methods, the probit model possesses the best and stable performance. The author reiterated that this outcome is subject to strict adherence to the multivariate normality assumption. Analogous to the conditionality given by Lin to the performance of the probit model over the others, Lo (1986) also found that if the research data satisfies the normality distribution assumption, the predictive ability of multiple discriminant analysis model will be higher than logit model, otherwise, the logit model outperforms the multiple discriminant analysis model in predicting financial distress. Contrary to Lo (1986), Lennox (1999), found that in a well specified model situation, the logit and probit models out-calls their multiple discriminate analysis counterpart as far as predictive accuracy is concern.

The purpose of predictive models is to give a good classification prediction of two distinct case of interest. In the case of this present study, the distinct groups are credit defaulters and non-defaulters. In essence, the models which are quantitative in nature are meant to accurately

distinguish good applicants (likely to repay) from bad applicants (likely to default) which makes it prudent to compare models in terms of their predictive accuracy in order to select the best classifier. Beasens et al. (2003) shows that, an improvement in accuracy of a fraction or percent might translate into significant future savings for the lending institutions. In this regard, it is noteworthy in credit scoring research such as this, for the researcher to compare the results of separate models, instead of relying on a single prediction technique.

So far, we have been reviewing literature on the various default prediction or scoring models. The chapter touched on the various variables that are crucial and significant for credit assessment and best predict default as well as the statistical models, that perform well in this regard. It appears that even though empirical proofs concerning the overall performance of prediction models exist, it will be difficult to generalize, meaning that models respond (in terms of predictive accuracy) differently to any kind of data used as well as the time the information is available (Ohlson, 1980) and also, regional differences. Hence, using existing classification accuracies as benchmarks for determining the acceptability of a model built based on a different sample appears misleading (Kealhofer, 2005). As a further step to this practice, this study employed the Press-Q statistic as a statistical standard to test the acceptability and validity of our models.

2.2.5 FURTHER REVIEW OF RELATED LITERATURE

Charalombous et al.,(2000),compared neural network algorithms which included feed forward networks, radial basis function, learning vector quantization and back propagation with logistic

regression in the prediction of the probability of default. They concluded that the neural networks produced a better prediction results.

Kolesar and Shower(1985) used mathematical programming to solve multicriteria optimization credit granting decision and compared it with linear Discriminant analysis. Although the results of mathematical modelling were violated, linear Discriminant analysis gave effective results.

In a study by Komorád (2002), logistic regression was compared to multilayer perceptron and radial basis function neural networks for credit scoring. These models were used and their performance tested on confidential data from a French bank. He found out that the multilayer perceptron neural network and the radial basis function neural network gave very similar results, but the basis function neural network performed the best

In a recent study, Fernandes et al. (2011) compare some different models to calculate probability of default in a low default setting. A data set consisting of a portfolio of low defaulting companies in Brazil was considered. There were 1,327 companies in the data set of which 50 defaulted. Four techniques were used to analyse the data, classical logistic regression, Bayesian logistic regression, limited logistic regression and an artificial oversampling technique. For the Bayesian logistic regression model, a non-informative prior was used. The prior was assumed to be normally distributed with zero mean and very large variance. A Gibbs sampler was used to solve the MCMC algorithm, however, the details of how this was done was not given. The four modelling procedures were compared using the area under the Response Operating Characteristic (ROC) curve, Gini coefficient and Kolmogorov-Smirnov statistics. The results showed that the four models considered gave very similar parameter estimates. However, after a bootstrap simulation was run to minimise the problem of the low number of defaults in the sample, the

results revealed that the Bayesian model presented a high level of performance with a lower bootstrap variance. The Bayesian logistic regression model was, therefore, considered as the best model in this situation.

François Coppens et al., (2007) assessed the performance of credit rating systems in the assessment of collateral used in eurosystem monetary policy operations. In their assessment, preference was given to back testing techniques as they happened to be the early warning tools for identifying performance problems in credit assessment systems. This could be useful in the context of the Eurosystem Credit Assessment Framework, in which various credit assessment sources can be employed to assess the credit quality standards of eligible collateral.

Altman,(1968) also assessed the analytical quality of ratio analysis using the discriminant function with ratios called the Z- score model. He finds that 95% of the data used was correctly predicted.

Kuldeep (2002) discussed and compared various methods for forecasting financial distress and credit ratings financial data relevant to a debt issue ratings was obtained from the publications of a premier credit rating agency in India. Findings clearly showed that financial performance data of the company before the issue has significant effect on credit rating by expert. Artificial Neural Networks (ANN) model was found superior to discriminant analysis model.

The Basel Committee on Banking Supervision (2006), researched into credit risk concentration. The committee concluded that Multi-factor models and possible refinements and extensions have the potential to offer a credible alternative to simulation-based assessments of economic capital, at least for diagnostic purposes.

Also, Kuldeep and Sukanto (2006) conducted a comparative study of prediction performances of an artificial neural network (ANN) model against a linear Discriminant analysis (LDA) with regards to forecasting corporate credit ratings from financial statement data. They found that since artificial neural network models can better deal with complex data sets and do not require restraining assumptions like linearity and normality, it is the preferred approach in corporate credit rating forecasts that uses large financial data sets.

Despite the fact that outcomes of Discriminant analysis can be predicted effectively, some difficulties arise when the assumptions underpinning it are violated and when the sample size used in the research is small. Horrigan and Orgler (1966) examined multiple linear regression in their analysis on credit scoring. However, they asserted that this method is not appropriate when the dependent variable of a model is categorical in nature. It is appropriate to represent such a qualitative dependent variable by a dummy. In short, to avoid problems such as biased and inconsistent estimates, generalized linear models (GLM) such as Poisson regressions were developed.

Young-Chan, (2005), researched into corporate credit rating analysis. His study applied support vector machines (SVMs) to the corporate credit rating problem in an attempt to suggest a new model with better explanatory power and stability. To serve this purpose, he used a grid-search technique with five-fold cross validation to find out the optimal parameter values of kernel function of SVM. In addition, to evaluate the prediction accuracy of SVM, he compared its performance with those of multiple discriminant analysis (MDA), case-based reasoning (CBR), and three-layer fully connected back-propagation neural networks (BPNs). The experiment results show that SVM outperforms the other methods.

Pompe and Feelers(1997),compared classification trees with linear discriminant analysis and neural network .The ten-fold cross validation results revealed that decision trees performed better than the logistic regression but not as the neural networks.

Dombolena and Khoury (1980) included the stability measures of the ratios to the discriminant analysis model with ratios. The stability measures included standard error of estimates, coefficient of variations and standard deviation of ratios over the past few years. The standard deviation was found to be the strongest measures of stability and accuracy of ratios was found to be 78% five years prior to failure.

Gilbert et al.,(1990) showed that in bankruptcy model developed with bankrupt random samples firms that failed from other financially upset firms when stepwise logistic regressions was used, can be distinguished.

The earliest study about statistical decision making for loan granting was published by Durand (1941) in his studies he applied Fisher's Discriminant analysis to evaluate the credit worthiness of individuals from banks and financial institutions. After this study, the Discriminant age of credit granting was started.

Myers and Forgy(1963) compared Discriminant analysis with stepwise multiple linear regression and equal weighted linear combination of ratios. In their study, both financial and non-financial variables were used. Firstly, the variables in nominal scale were scaled into a "quantified" scale from best to worst. Surprisingly, they found that equal weighted functions' predictive ability is as effective as other methods

Discriminant analysis was not the only technique in 1960's, there was also the time varying decision making models built to avoid unrealistic situations by modeling the applicant's default

probability varying overtime. The first study on time varying model was introduced by Cyert et al. (1962)

Srinivasan and Kim (1981) built a model for evaluating profitability with Bayesian that updates the profitability of default overtime. The relative effectiveness of other classification procedures was examined.

In 2005, Bensic et al., evaluated the Bayesian network classifier using Markov chain Monte Carlo. Different Bayesian network classifiers such as naive Bayesian classifier, tree arguments naive Bayesian classifier and unrestricted Bayesian network classifier by means correctly classified percentages and area under Receiver Operating Characteristic curve were assessed. They were found to be good classifiers. Results were parsimonious and powerful for financial credit scoring. Coats and Fants (1993) presented a new method to recognize financial distress patterns in 1this, Altman's ratios were used to compare with Discriminant analysis and his algorithms was found to be more accurate. The genetic programming intelligent system was used in many research.

Huang et al.,(2005) examined a two stage genetic programming method. They concluded that it is a sufficient method for loan granting. In credit assessment, the object of banks or financial institutions is to decrease the credit risk by minimizing expected cost of loan granting or rejecting. The first study of such a mathematical optimization problem was programmed by Wilcox (1973) . He utilized a dynamic model that is relating bankruptcy in time t with financial stability at $t-1$

Miller E .J (2005) found out that statistical models for risk analysis and forecasting credit losses on loan and leasing portfolios were used by major financial institutions, to assess credit risk

associated with loans and leases in different market segments, and to help in the determination of appropriate reserves against credit losses.

Martinez. (1996) carried out a research on development of statistical models to identify new adopters of advanced services for a major telecommunications company. He pointed out that the resulting statistical models were used in planning deployment of new digital switches to increase capacity at telephone line centres throughout a company's five state service area. He also asserted that they were used to individualize responses to customer telephone inquiries based on geo-demographic data and account activity ,effectively identifying individual customers who were most likely to purchase high-revenue but discretionary services

Niinimaki (2004) in his paper entitled "The effects of competition on banks' risk taking" found that the magnitude of risk taking depends on the structure and side of the market in which competition takes place. He also concluded that if the bank is a monopoly or banks are competing only in the loan market, deposit insurance has no effect on risk taking. Banks in this situation tend to take risks, although extreme risk taking is avoided. In contrast, introducing deposit insurance increases risk taking if banks are competing for deposits. In this case, deposit rates become excessively high, thereby forcing banks to take extreme risks. Several risk-adjusted performance measures have been proposed (Heffernan, 1996;Kealhofer, 2003). The measures, however, focus on risk-return trade-off, i.e. measuring the risk inherent in each activity or product and charge it accordingly for the capital required to support it. This does not solve the issue of recovering loanable amount.

Effective system that ensures repayment of loans by borrowers is critical in dealing with asymmetric information problems and in reducing the level of loan losses, thus the long-term success of any banking organization (Basel, 1999; IAIS, 2003). Effective CRM involves

establishing an appropriate credit risk environment; operating under a sound credit granting process; maintaining an appropriate credit administration that involves monitoring process as well as adequate controls over credit risk (Basel, 1999; Greuning and Bratanovic, 2003). It requires top management to ensure that there are proper and clear guidelines in managing credit risk, i.e. all guidelines are properly communicated throughout the organization; and that everybody involved in Credit Risk Management (CRM) understand them.

Considerations that form the basis for sound CRM system include: policy and strategies (guidelines) that clearly outline the scope and allocation of a bank credit facilities and the manner in which a credit portfolio is managed, i.e. how loans are originated, appraised, supervised and collected (Basel, 1999; Greuning and Bratanovic, 2003; PriceWaterhouse, 1994). Screening borrowers is an activity that has widely been recommended by, among others, Derban et al (2005). The recommendation has been widely put to use in the banking sector in the form of credit assessment. According to the asymmetric information theory, a collection of reliable information from prospective borrowers becomes critical in accomplishing effective screening.

The assessment of borrowers can be performed through the use of qualitative as well as quantitative techniques. One major challenge of using qualitative models is their subjective nature (Bryant, 1999; Chijoriga, 1997). However, borrowers attributes assessed through qualitative models can be assigned numbers with the sum of the values compared to a threshold. This technique is termed as “credit scoring” (Heffernan, 1996; Uyemura and Deventer, 1993). The technique cannot only minimize processing costs but also reduce subjective judgments and possible biases (Kraft, 2000; Bluhm et al., 2003; Derban et al., 2005). The rating systems if meaningful should signal changes in expected level of loan loss (Santomero, 1997). Chijoriga (1997) concluded that quantitative models make it possible to, among others, numerically

establish which factors are important in explaining default risk, evaluate the relative degree of importance of the factors, improve the pricing of default risk, be more able to screen out bad loan applicants and be in a better position to calculate any reserve needed to meet expected future loan losses. Clear established process for approving new credits and extending the existing credits have been observed to be very important while managing Credit Risk (Heffernan, 1996).

Further, monitoring of borrowers is very important as current and potential exposures change with both the passage of time and the movements in the underlying variables (Donaldson, 1994; Mwisho, 2001), and also very important in dealing with moral hazard problem (Derban et al., 2005). Monitoring involves, among others, frequent contact with borrowers, creating an environment that the bank can be seen as a solver of problems and trusted adviser; develop the culture of being supportive to borrowers whenever they are recognized to be in difficulties and are striving to deal with the situation; monitoring the flow of borrower's business through the bank's account; regular review of the borrower's reports as well as an on-site visit; updating borrowers credit files and periodically reviewing the borrowers rating assigned at the time the credit was granted (Donaldson, 1994; Treacy and Carey, 1998; Tummala and Burchett, 1999; Basel, 1999; Mwisho, 2001).

Tools like covenants, collateral, credit rationing, loan securitization and loan syndication have been used by banks in developing the world in controlling credit losses (Benveniste and Berger, 1987; Greenbaum and Thakor, 1987; Berger and Udell, 1992; Hugh, 2001). It has also been observed that high-quality CRM staffs are critical to ensure that the depth of knowledge and judgment needed is always available, thus successfully managing the credit risk in Commercial Banks (Koford and Tschoegl, 1997; Wyman, 1999).

Donaldson (1994) and Jeremy and Stein (1999) observed that computers are useful in credit analysis, monitoring and control, as they make it easy to keep track on trend of credits within the portfolio. Marphatia and Tiwari (2004) argued that risk management is primarily about people how they think and how they interact with one another. Technology is just a tool; in the wrong hands it is useless. This stresses further the critical importance of qualified staff in managing credit risk.

Credit scoring is essentially a classification problem where applicants are classified into different groups. According to Thomas (2009) statistical classification techniques started when Fisher (1936) developed one of the first successful classification models to classify three different types of the iris flower. He used different physical measurements of the flower to discriminate between the three types of Iris flowers. Durand (1941) was then the first to recognise that these statistical classification techniques could be used to classify good and bad loans. Before this, Thomas (2009) states that financial institutions based decisions on whether to grant credit subjectively. When credit cards were introduced in the 1960s, the usefulness of credit scoring started to be realized. Because of the large number of people applying for credit cards, automation of the credit application procedure seemed to be the only solution. When the financial institution introduced the credit scoring model they found that the model performed a lot better than the previous (subjective) judgment scheme. The result was that, as Thomas (2009) states, default rates dropped by 50% or more. In the 1980s the success of credit scoring in credit cards meant that financial institutions started using scoring methods for other products too such as personal loans, home loans and business loans.

The subprime mortgage crisis caused a global recession in 2007. This crisis proved that financial institutions did not fully understand the risks they were taking on. According to Rona-Tas and Hib (2008), a credit score generally used by financial institutions in the United States is the Fair Isaac Company (FICO) score. They state that these FICO scores grew steadily from 2000 to 2005. This made subprime borrowers appear less risky. Possible reasons for these inflated FICO scores include the data used to construct the FICO scores are historical data, not necessarily only from subprime lenders, and banks putting pressure on credit rating agencies to inflate their credit rating scores. The reason why banks would put pressure on credit rating agencies is that they were able to sell their loans to investors. Thus, the banks would want to grant as many loans as possible and then sell them to investors.

Because credit scoring is fundamentally a classification problem, there are a number of methods available for credit scoring. Hand and Henley (1997) give a review in statistical classification methods in consumer credit scoring. They first give an overview of credit scoring and building a scoring model including some associated problems. They mention that scorecards are classifiers which “use predictor variables from application forms and other sources to yield estimates of the probabilities of defaulting” (Hand and Henley, 1997, p. 524). A threshold on this probability is then obtained, classification applied and a decision on whether a loan should be granted or not, can be given on a new applicant. They further explain that when building a credit scoring model, three approaches to selecting the variables are commonly used, as follows:

- Using expert knowledge. Where an experienced industry expert decides what variables will fit the data well;

- Using stepwise statistical methods such as forward/backward stepwise methods which sequentially add/delete variables;
- Selecting individual variables by using a measure of difference between the distributions of the good and bad risks on that variable.

A major problem in credit assessment is that of reject inference. Mok (2009) explains that complete data are only available for accepted applicants. This means that the observed behaviour of an applicant is only available for the accepted applicants. Because the accepted applicants were already accepted through an existing scoring model, we have biased data. It would be better to build a model where everyone is accepted and their behaviour is observed. However, this is unfeasible for banks. Therefore to solve this bias problem, reject inference is proposed. According to Mok (2009) this is “the process of estimating the risk of default for loan applicants that are rejected under the current acceptance policy” (Mok, 2009, p. 1). Crook and Banasik (2002) suggest finding a cut-off to classify the rejects whether good or bad then include these rejected applicants in the new model.

Hand and Henley (1997) give an overview of different models used for credit scoring. These methods are discriminant analysis, regression analysis, logistic regression, probit analysis, mathematical programming, recursive partitioning (decision trees), expert systems, neural networks, nonparametric smoothing methods and time varying models. They state that “there is no overall best model” (Hand and Henley, 1997, p. 535). This is because the best model depends on the data structure. It is also mentioned that neural networks might provide a good modelling approach when there is poor understanding of the data structure. However, these models provide a “black box” approach and usually no understanding can be gained from the model. There have been a number of studies which compare these methods in credit scoring. Altman et al. (1994)

provided one of the first investigations of neural networks in credit scoring. Neural networks were compared to linear discriminant analysis (LDA) and it was found that LDA performed better. Desai et al. (1996) obtained different results. Using a credit union data set, a neural network performed better than LDA but did not perform significantly better than logistic regression.

Thomas (2009) claims that logistic regression is the most commonly used method for the construction of scorecards. Logistic regression is part of a wider class of generalized linear models (GLMs) as shown by Nelder and Wedderburn (1972). The reason for this is that the binomial distribution, which is the distribution of the response in logistic regression, is part of the exponential family of distributions. GLMs include a number of models such as normal linear regression, logistic regression, Poisson regression etc. One of the first applications of logistic regression to credit scoring is given by Steenackers and Goovaerts (1989). Based on data from a Belgian credit company they develop a logistic regression model. Nineteen predictor variables were utilized and then using stepwise logistic regression, 11 variables were chosen for a final model. Steenackers and Goovaerts (1989) also mentioned that the model relies on historical data. Therefore, a periodical review of the model is necessary to adjust for shifts in the underlying factors. To solve this problem in credit scoring, Whittacker et al. (2007) developed a Kalman filter for a credit scorecard. Here, the scorecard is updated by combining the new applicant data with the previous best estimate. A Bayesian approach can also be used to update a model - the posterior distribution is updated as soon as new information becomes available. Greenberg (2008) stated that Bayesian updating is a very attractive feature of Bayesian inference. With Bayesian logistic regression, numerical methods are used to update the model. The reason for this is that conjugate priors (the posterior distribution comes from the same family of the prior

distribution) do not exist. A popular method used to update the model is the Markov Chain Monte Carlo (MCMC) method.

Mira and Tenconi (2004) developed a Bayesian hierarchical logistic regression model to predict credit risk of companies which fall in different sectors. They used fairly vague priors for the parameters of the model - priors centred at zero with large variances. They used MCMC methods to estimate the model. One method was the delayed rejection (DR) strategy with a single delaying step. This is similar to the MH algorithm but there is another chance to accept a move. Here, upon rejection of a move, a second stage candidate is proposed and accepted with a probability that preserves the so-called detailed balance condition. It is claimed that the DR estimates have a smaller variance than the estimates obtained via MH. The DR strategy has a shorter run time than the standard MH algorithm. This is the principle advantage of DR. Mira and Tenconi (2004) show how simulation using the delayed rejection strategy outperforms the standard MH algorithm in terms of efficiency of the estimates. They also show, using cross validation, that the Bayesian model outperforms the classical logistic regression model.

In another study, Ziemba (2005) showed how a (existing) generic scoring model can be updated using Bayesian methods. He mentions that this is a preferred solution in the banking industry when an international bank is opening a branch in a new country, a financial institution starts offering new services or a bank is offering services to a new group of customers. Therefore, unlike Mira and Tenconi (2004) where a fairly vague prior was used, Ziemba (2005) uses an existing model as a source of prior information for the model parameters. He assumes that these prior parameters are normally distributed. Ziemba (2005) considers a case where a new procedure is introduced to the credit scoring - customers were required to complete an extended application form resulting in an increase in the number of predictor variables. The parameters of the model

used before the change in procedure were used as priors for the parameters in the new model. For the additional variables under the new procedure, vague priors were used. The model was then updated as new data became available. Like Mira and Tenconi (2004) the Metropolis-Hastings algorithm is used to obtain the posterior but the DR was not investigated. Results are given for different amounts of new data. It was found that, when the amount of new data is smaller, including prior information results in much better accuracy than when the amount of new data is larger. The rate of this accuracy decreases as the amount of new data increases and prior information becomes less relevant.

In a similar study, Löffler et al. (2005) proposed a Bayesian method for banks to improve their credit scoring models by imposing prior information. This methodology enables banks with small data sets to improve their default probability estimates by making use of prior information. This might occur when a bank introduces a new rating system or expands into a new market as Ziemba (2005) mentions. Löffler et al. (2005) set up a simulation study in order to investigate the Bayesian approach. They bootstrapped from an initial small data set. A large data set was simulated and this was labelled “external” data. Prior information for regression coefficients were obtained from these data by running a logistic regression. A smaller data set was then simulated and named “internal” data. A logistic regression was run on this “internal” data, as well as a Bayesian logistic regression using the parameters from the “external” data as priors. This approach is very similar to Ziemba (2005) where a generic scorecard is updated. Here, the model from the “external” data can be seen as a generic scorecard. Löffler et al. (2005) found that when there is no structural difference between the “internal” and “external” data the Bayesian logistic regression model performs significantly better. In a more realistic case, there will be some structural differences between the “internal” and “external” data. They imposed structural

differences by assuming that some variables are missing in the “external” or prior data set. It was found that the Bayesian logistic regression model still performs better than the logistic regression model when there are structural differences. Like Ziembra (2005) it was found that as the size of the “internal” data increases the relevance of prior information decreases.

In a different study, Wilhelmsen et al. (2009) compared the method of Integrated Nested Laplace Approximation (INLA) to MCMC methods for Bayesian modelling of credit risk. The MCMC method they used is the MH algorithm. Therefore, like Mira and Tenconi (2004) this is a comparative study between two methods to sample from the posterior. INLA can be used as an alternative to MCMC methods. They used the Bayesian formulation of logistic regression. Like Ziembra (2005) normal priors were used for the regression coefficients. INLA only allows the use of normal priors. They gave an outline of how priors for the regression coefficients can be obtained from prior information on the default probabilities. They suggested that a beta distribution for the default probability should be assumed. Greenberg (2008) stated that the beta distribution is a good choice for a prior since it is defined on the relevant range and it can produce a wide variety of shapes. Data from a Norwegian bank were used to compare INLA to MCMC when a vague and specific prior is used. They found that INLA and MCMC gave approximately the same posterior results for their particular data set, but mentioned that results may differ in other situations. They also indicated that there may be convergence issues with MCMC.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

At this stage of the study, the researcher explores the methodological framework in dichotomous dependent regression analysis. Key issues were also addressed using the probit and logit models in credit risk modeling. The chapter continues by discussing the explanatory variables as well as their impact on probability of default. Aside these, the section touches on the sample size for the estimation as well as model performance assessment procedures. It also entails the source of data for the study, and an extensive chronology of the data analysis procedure.

3.1 The Binary Dependent Variable

In models where the dependent variable (Y) is qualitative (dummy) in nature, the objective then will be to find probability of one thing happening against the other. In this case, the probability has to do with defaulted and non-defaulted firms. Hence, qualitative response regression model are often known as probability models (Gujarati, 2004)

The two groups of interest in this research are: defaulted and non-defaulted firms which will be represented as a binary variable. A binary variable is a variable that has arbitrary units assigned to it in such a way that it will be possible to approximate the variations in the factor we want to express quantitatively (Koutsoyiannis, 2001). These arbitrary units are 1 and 0 to represent the two groups of interest in this study which are defaulted and non-defaulted firms.

According to Hair et al. (2006), it does not matter which group is assigned the value of 1 or 0, but the assignment must be noted for the purpose of interpretation of the coefficients or results. In this instance, the two dependent groups of interest in this research are represented below as:

$$Y = \begin{cases} 1, & \text{if firm } i \text{ defaulted} \\ 0, & \text{if otherwise} \end{cases}$$

3.2 The Logit Model

In the application of logistic regression model to credit scoring, the objective is to find the conditional probability of a good or bad loan, given the values of the independent variables pertaining to a particular credit applicant (Lee and Chen, 2005).

By considering a linear probability model (LPM);

$$P_i = E(Y = 1 / X_i) = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1} \quad (3.0)$$

Where P_i is the Probability of default; $Y = 1$ means firm i defaulted; X_i are the set of predictor variables where $(X_i = 1, 2, 3, \dots, n)$ and β_1, \dots, β_k represents the coefficients of the explanatory variables.

Now let's consider the following representation of loan default

$$P_i = E(Y = 1 / X_i) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_i)}} \quad (3.1)$$

For ease of exposition, let us write equation (3.1) as

$$P_i = \frac{1}{1 + e^{-z_i}} = \frac{e^z}{1 + e^z} \quad (3.2)$$

Where $Z_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1}$

The new equation, (3.2) represents the cumulative logistic distribution function. The Z_i ranges from $-\infty$ to $+\infty$, P_i ranges between 0 and 1 and that P_i is non-linearly related to Z_i (Gujarati, 2004). This therefore violates the linearity assumption and as such, the ordinary least squares (OLS) estimation breaks down. Due to the non-linear nature of equation (3.2) another procedure, “Maximum Likelihood Estimation” (MLE) procedure is used in an iterative manner for estimation (Hair et al., 2006). Thus the method maximizes the likelihood that an event will occur. This procedure was followed in this study to estimate the model. Now in order to make equation (3.2) the probability of default linear so as to meet the linearity assumption in P_i is the probability of loan default, then the probability of non-default ($1-P_i$) is

$$1 - P_i = \frac{1}{1+e^{Z_i}} \quad (3.3)$$

Therefore, we can write $\frac{P_i}{1-P_i}$ as $\frac{\frac{e^{Z_i}}{1+e^{Z_i}}}{\frac{1}{1+e^{Z_i}}} = e^{Z_i} \frac{1+e^{Z_i}}{1+e^{Z_i}} = e^{Z_i}$ (3.4)

Where $\frac{P_i}{1+P_i}$ is the odds ratio in favour of loan default. The odds ratio is the ratio of the probability that a firm will default to the probability that it will not default.

By taking the natural log of equation (3.4), we obtain:

$$\ln\left(\frac{P_i}{1-P_i}\right) = Z_i \quad (3.5)$$

Therefore, the theoretical logit model (L_i) can be stated as:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i \quad (3.6)$$

Where $Z_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1}$

For the purpose of this estimation, I will state the logit model in this form:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1} + \varepsilon_i \quad (3.7)$$

Where ε_i is the error term

3.2.1 Theoretical Logit Model

$$L_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 + \beta_5 X_4 + \beta_6 X_5 + \beta_7 X_6 + \beta_8 X_7 + \beta_9 X_8 + \beta_{10} X_9 + \beta_{11} X_{10} + \beta_{12} X_{11} + \beta_{13} X_{12} + \beta_{14} X_{13} + \beta_{15} X_{14} + \beta_{16} X_{15} + \varepsilon_i \quad (3.8)$$

Where; $L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1} + \varepsilon_i$

X_1 = Earning to Interest Expense

X_2 = Total Liabilities/ Total Assets

X_3 = Cash/Total Assets

X_4 = Working Capital/Total Assets

X_5 = Current Assets/Current Liabilities

X_6 = EBIT/Total Assets

X_7 = Retained Earnings/Total Assets

X_8 = Accounts receivable/Total Liabilities

X_9 = Operating Income/Total Assets

X_{10} = Current liability to total liabilities

X_{11} =Earning to interest

X_{12} =Net current asset

X_{13} =Total liability to net current ratio

X_{14} =Cash to current liability

X_{15} =Total asset

ε_i is the error term

3.2.2 Assumptions of the Logistic Regression

The logistic regression employs binomial probability theory in which there are only two values to predict (Gujarati, 2004). One implicit assumption of the regression procedure is that, the binomial distribution describes the distribution of the errors that equal the actual dependent variable (Y) minus the predicted Y (Peng et al., 2002). The binomial distribution is also the assumed distribution for the conditional means of the dichotomous outcome. This assumption implies that the same probability is maintained across the range of predictor values. However, this assumption is taken to be robust as long as the sample or observations are random or independent of each other (Peng et al., 2002). The sample of firms used in this study does not have inherent dependence among themselves. Thus, the firms used are all independent of each other (autonomous). In addition, the sample selection was randomly made without prejudice to any specific firm. Hence, the binomial assumption can be said to be robust in our logistic analysis since there is mutual exclusivity among the group of firms. Moreover, sampling bias in general

does not appear to affect the statistic inferences or overall classification rates of models (Zmijewski, 1984).

3.3 The probit model

The estimation model that emerges from the normal cumulative distribution function (CDF) is what is known as the Probit model which is sometimes called the normit model (Gujarati, 2004). Put in a different way, the binomial Probit model is an estimation technique for equations with dummy dependent variables that avoid the unboundedness problem of the linear probability model by using a variant of the cumulative normal distribution (Studenmund, 2006)

To develop the probit model, let us assume that the credit default probability of the i^{th} firm depends on a latent variable l_i that is determined by one or more predictor variables. In this study, the predictor variables are accounting ratios.

Let us express the latent (l_i) as:

$$l_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1} \quad (3.9)$$

Where β_1, \dots, β_k represents the coefficients of the explanatory variables and X_1, \dots, X_k symbolises the explanatory variables.

From here, the latent (l_i) is the propensity of a firm defaulting. The propensity will lie between $-\infty$ to $+\infty$ while the probability will lie between 0 to 1

The CDF is the probability transformation of I_i that helps us to achieve the purpose of keeping the probability between 0 and 1 and also make sure that I_i is between $-\infty$ to $+\infty$ thus,

$$P_i = PDF(F)[l_i] = F(\beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1}) \quad (3.10)$$

Where $F(l_i) \equiv$ cumulative normal distribution function or standard normal which is $Z \sim N(0,1)$ random variable evaluated at l_i .

$$F(I_i) = P_i(I^* \leq I_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{I_i} e^{-z^2/2} dz \quad (3.11)$$

Where $l_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1}$

; Z is a standardized normal variable: P_i is the probability that the dummy dependent variable (probability of default)= 1: I^* is a critical or threshold level of I_i , such that if I_i , exceeds I^* the firm will default, otherwise it will not.

As different as the probit model looks from the logit model, it can be written to look quite familiar (Studenmund, 2006) as shown in equation (3.12) below

$$I_i = F^{-1}(P_i) = \beta_1 + \beta_2 X_1 + \beta_3 X_2 \dots + \beta_k X_{k-1} \quad (3.12)$$

Where F^{-1} is the inverse of the normal cumulative distribution function (CDF) or the normal distribution.

3.3.1 Theoretical Probit Model

$$L_i = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 + \beta_5 X_4 + \beta_6 X_5 + \beta_7 X_6 + \beta_8 X_7 + \beta_9 X_8 + \beta_{10} X_9 + \beta_{11} X_{10} + \beta_{12} X_{11} + \beta_{13} X_{12} + \beta_{14} X_{13} + \beta_{15} X_{14} + \beta_{16} X_{15} + \varepsilon_i \quad (3.13)$$

Where;

X_1 = Earning to Interest Expense

X_2 = Total Liabilities/ Total Assets

X_3 = Cash/Total Assets

X_4 = Working Capital/Total Assets

X_5 = Current Assets/Current Liabilities

X_6 = EBIT/Total Assets

X_7 = Retained Earnings/Total Assets

X_8 = Accounts receivable/Total Liabilities

X_9 = Operating Income/Total Assets

X_{10} = Current liability to total liabilities

X_{11} = Earning to interest

X_{12} = Net current asset

X_{13} = Total liability to net current ratio

X_{14} = Cash to current liability

X_{15} = Total asset

ε_i is the error term

3.3.2 Assumption of the Probit Regression

One tacit assumption of the probit model is that, it follows the normal distribution (Gujarati, 2004). Secondly, it is assumed that the error term is homoscedastic or constant across all observations (Cleves, 2002), See discussion in chapter four on how these issues were assessed.

3.4 The Explanatory variables

Careful examination of the current literature facilitates selection of a variety of financial ratios with a significant influence on corporate default rate. Financial distress models in themselves do not have a theory behind them; instead they seem to employ an ad hoc pragmatic approach, using easily available as well as theoretically and empirically justifiable accounting data to predict default (Khatwani et al., 2006; Bhimani et al., 2010). Traditionally, the most convenient method of summarizing the large amounts of financial data needed to comprehend any individual company's internal condition has been through financial ratios, used extensively by both practitioners and researchers (Smith and Liou, 2007)

In many studies, specific ratios were selected by the following criterion: population in the literature by virtue of their consistent significance and performance, and common usage by financial analysis or practitioners in the field. All the same, in this study, following the above criterions a number of variables from literature were drawn together to form the independent variable for this study (e.g. Altman, 1968; Khatwani et al., 2006 Latman and sabato, 2007; Chijoriga, 2011) . Below are the Categories and descriptions of independent variables used in the models

3.4.1 Financial Leverage Ratios

The extent of leverage is regularly used as an indicator of a company's ability to meet its debt obligations and remain solvent (Psillake et al., 2010; Maria et al., 2011). In this study, two ratios have been considered under the leverage category. These are:

- ***Earning to Interest Expense (Debt Coverage ratio) (X_1):*** The debt coverage or interest coverage ratio is calculated by dividing a company's earnings before interest and taxes by the interest expense. This ratio measures how well a company's earnings cover its interest payments on debt or the firm's ability to meet the interest charges on its debt and avoid future financial difficulties (i.e. to generate revenue to service its debt) (Pierson et al., 1990). Measuring debt levels permits the assessment of the longer-term sustainability of a company because high levels of debt could affect the long-term profitability if the company is unable to make its interest payments. This ratio measures how many times the company is earning more than its interest expense and as such, high ratios indicate low financial risk (Solomon and Pringle, 1980). We thus expect a negative relationship between earnings coverage ratio and the likelihood that a firm will default.

- ***Total Liabilities/Total Assets (leverage ratio) (X_2):*** This is calculated by dividing the total liabilities of the company by the total assets. Since assets are either funded by debt or equity, the higher the financial leverage, the riskier it is for the firms, as more assets are funded through debt (Maria et al., 2011). The probability of bankruptcy or default for any borrower increases as the amount borrowed increases (Stiglitz, 1972) Also, failing firms, are generally expected to carry more debt in their capital structure (Zavgren, 1985) as there is a real possibility of

bankruptcy if a firm takes on “too much” debt (Stiglitz, 1972) Hence, a direct link between the ration and the financial risk of default is expected.

3.4.2 Liquidity Ratios

It is a financial performance matrix that is used to determine a company’s ability to pay off its short term debt obligations. Liquidity provides the defensive cash and near cash resources for firms to meet claims for payment (Tinsley, 1970). A firm experiencing consistent operating losses will have shrinking assets or equity (Altman, 1968) individuating that the inability of a corporation to generate cash from its operations over time may cause a default on its debt (Rujoub et al., 1995). Generally speaking, the higher the ratio, the stronger the firm’s liquidity, and the greater the probability of success of the firm. In this study, a number of ratios that comprise liquidity have been presented namely: cash to total assets ratio, working capital to total assets ratio, and current assets to current liabilities ratio.

- **Cash/Total Assets (X_3):** This ratio measures the proportion of Total Assets that is funded by Cash (Tinsley, 1970). A higher ratio exhibits a higher liquidity for a firm. This is important in view of the fact that the firm will have to make payments on debts/liabilities with cash. Hence the more the availability of cash to the firms, the less the likelihood is to default. Hence, an inverse relationship is expected with default risk.
- **Net Working Capital/Total Assets (X_4):** This ratio examines the ability of the company to meet emergencies. Net working capital in this study is measured as the difference between current assets and current liabilities. Typically, a firm experiencing consistent operating losses

will have shrinking current assets in relation to total assets (Altman, 1968) Generally, the higher the ratio, the better equipped the company is in its ability to meet emergencies. Hence, an inverse relationship is expected between this variable and probability of default.

- ***Current Assets/Current Liabilities (Current Ratio) (X_5):*** It is commonly used to measure short-term solvency, to evaluate the ability of a company to pay its debts as they become due. Generally, the higher the ratio, the greater will be the firms' ability to cover its short term financial obligations. However, excessively higher ratio will mean that greater proportion of the firms' resources is tied up in relatively unproductive assets which may have an adverse effect on profitability (Pierson et al., 1990). As such, firms must seek to balance the benefits of high levels of liquidity that guard against liquidity crises with the costs of high liquidity that may adversely affect investment returns (Saunders and Cornett, 2007). It is thus expected that on average, firms with more net liquid assets will be less likely to default.

3.4.3. Profitability Ratios

The aim of profitability ratios is to measure the effectiveness of management in using a company's resources to generate returns (Pierson et al., 1990) and are also used as measures of firms performance (Joseph and Lipka, 2006). As emphasised by Altman (1968), a firm's ultimate existence is based on the earning power of its assets. A negative relationship between profitability ratios and the likelihood that a firm will default is therefore expected. For the purpose of this study, two ratios have been considered under this category. These include;

- ***EBIT/Total Assets (ROA) (X_6)***: ROA is measured by earnings before interest and tax (EBIT) divided by total assets. It measures the firm's operating efficiency in generating profits from its assets, prior to the effects of financing (Damodaran, 2006). Additionally, given the importance of generated returns to the health of a business, creditors typically rely on measures of profitability when extending credit or renegotiating repayments to estimate the return generated by the firm on borrowed capital (Claessens et al., 2003). A negative relation is therefore expected with default probability.
- ***Retained Earnings/Total Assets Ratio (X_7)***: Retained earnings are the total reinvested earnings or losses of a firm over its entire life. This is a measure of cumulative profitability over time, and is an important predictor of financial crisis (Pindado et al., 2008). This measures the firm's ability to accumulate earnings using its assets. More so when past profitability can be useful in predicting future results and capacity for self-financing (Routledge and Gadenne, 2000). A higher ratio is preferable because it indicates that the firm is able to retain more earnings and hence can meet its debt obligations. It is calculated by dividing the retained earnings by the total assets.

3.4.4. Activity Ratio (X_8)

Activity ratios measure the effectiveness of a company's use of its assets (Pierson et al., 1990). Such ratios are used to measure the amount of credit given and received by a company (Maria et al., 2011). In this study, it is given as accounts receivable divided by total liabilities. Here, an increasing ratio means that a large fraction of the firms' own debt can be repaid by outstanding

claims. It is therefore anticipated that the higher the ratio, the better the firm's ability to pay its outstanding debts (Thus the default probability should decrease with this ratio).

3.4.5 *Asset turnover Ratio (X_9)*

In terms of the efficient use of firm assets, it is important to analyse asset turnover. Asset turnover measures how well a company uses its assets to generate sales (Maria et al., 2011). This is measured by dividing the operating income of the company by its total assets (Psillaki et al., 2019) . An efficient company will generate a higher level of sales with a given level of total assets than its less efficient competitor hence a higher ratio will mean low default risk. Thus, a negative relationship is expected between the ratio and the likelihood of default.

3.4.6 *Current liabilities to total liabilities (X_{10})*

Liabilities are unavoidable in the operations of any firm. Notwithstanding, its level and how it can affect the position of the firm is critical to the sustainability of the firm. A higher ratio indicates that the firm's current liabilities are less as compared to the total liabilities. A lower ratio is hence preferable.

3.4.7 *Earning to interest (X_{11})*

As indicated earlier, firm earnings is essential to the growth and sustainability of any firm. This ratio is used to ascertain how a company's earnings and interest blend to cover its outstanding

debts when due. The higher the earnings to the interest, the better it is for the firm. Thus, there will be enough earnings to cover interests payable. Such a firm is hence seen as less likely to default or less risky in terms of credit.

3.4.8 *Net current asset (X_{12})*

Current assets are seen in finance as the operational machinery that can be used to generate cash and also indicate the liquidity of the firm. The net current assets ratio shows the strength of firms in terms of their current assets. Per the importance of this variable, a firm that is less likely to default or less risky will have a higher current assets value as compared to its risky and un-creditworthy counterpart.

3.4.9 *Total liability to total current Ratio (X_{13})*

It can be recalled that liabilities are part of the operations of companies. Thus, they are issues that will be faced in the operation of any firm. This ratio is used to measure how well or the ratio of the firms' liabilities is from their net current position. A higher position or ratio shows that more of the firms' liabilities constitute its net position and vice-versa.

3.4.10 *Cash to Current liabilities (X_{14})*

In debt payment, cash is essential since it is the mode of payment. This shows the ratio of cash to current liabilities. It is meant to ascertain how much cash it is to cover the current liabilities of a firm. A higher ratio indicates that the firm in question has more cash to meet current liabilities. Such a firm can be described as less risky as compared to the one that will have a lower ratio

which will mean that the firm will have less cash to cover its liabilities when due hence highly risky.

3.4.11 Total asset (X_{15})

The size of the firm is seen in finance as one of the key variables to the integrity of a firm. It is believed that bigger firms are more sustainable and credible. In this study, the sizes of the firms were determined by using their total assets. The higher the asset level of the firm, the bigger it is and the less the likelihood of it failing or defaulting. It is asserted that bigger firms have built credibility over time and per their size, they have bigger capacity to meet impending contingencies. In short, it is thought that bigger firms are less likely to fail as compared to smaller ones.

3.5 Data source

The loan portfolio of a private commercial bank in Ghana served as the data repository for this study where historical data set of financial statements of a number of firms who had sourced credit from the bank was gathered.

3.6 Population of the Study

The population of interest in any study is typically a group of entities or persons who poses a distinct set of characteristics which enables the collection of useful information deemed appropriate by the researcher through which inferences are made (Malhotra, 2007). In this study, the population comprises of firms who had sourced credit from a private commercial bank in

Ghana. In their distinct characteristics, some of the firms performed well (non-default) in servicing their debts while others performed poorly and eventually defaulted.

3.7 Sample Size

Hair et al., (2006) suggests that the minimum sample for any meaningful dependence technique estimation must be in ratio of 5:1 which means a minimum of five (5) observations each to an independent variable. In this study, secondary data on three hundred and seventy seven (377) firms comprised the total sample with fifteen (15) independent variables. Under the total sample, two subsamples were created (split sample);

- i. The analysis sample: This was used to estimate the Probit and logit models and
- ii. The holdout sample: Used for validation purposes.

Reichert et al. (1983) suggest that while one should avoid using extremely small test or validation samples, reliable results can be achieved using relatively modest holdout samples in the range of 20 to 30 percent. In our study, we used approximately 23 percent (86) of the total sample as the holdout sample which means that the remaining 77 percent, (291) served as the estimation sample.

3.8 Assessing Overall Model Fit

Model fit in binary dependent models such as the logit and probit traditionally uses the “pseudo R^2 ” and the log-likelihood ratio (LR) as measures of overall fit. A subsequent model fit test which draws on the predictive accuracy (i.e. actual prediction of the dependent variable) referred to here in this study as probability of default, is the Hosmer and Lemeshow (2000) goodness-of-fit test. The test divides the cases/sample into equal classes (approximately 10 in the case of this study). Then the number of actual and predicted event is compared in each class with the chi-square statistics (Hosmer and Lemeshow, 2000). It is a post estimation test that assesses the overall significance/fit of the regression model (probit and logit). The test was carried out in this study as a diagnostic check to our model fits. The test statistic follows a χ^2 distribution with $g - 2$ degrees of freedom and is defined as:

$$H_L = \sum_{k=1}^g \frac{(O_k - N_k \Pi_k)^2}{N_k \Pi_k (1 - \Pi_k)} \quad (3.14)$$

Where H_L is the estimated statistics; g is total number of groups; N_k is number of observations (total frequency of object) in the k^{th} group; O_k is the total frequency of event outcomes in the k^{th} group; and Π_k is the average estimated predicted probability of an event outcome for the k^{th} group.

3.9 Model Predictive Performance Assessment

In testing the predictive ability or performance of the logit and probit models, the classification accuracy or percentage correctly classified (PCC) of both the in-sample and out-of-sample results were compared. This is done to provide a fair idea of model choice (Thomas et al., 2005; Hair et al., 2006). To complement the classification accuracy measure of predictive accuracy, the study

also assessed the performance of the models using the Receiver Operating Characteristic (ROC) curve which yielded the area under the ROC curve (AUC) (see also Bhimani et al., 2010) which has been argued to provide a better means of model performance/predictive assessment (Thomas et al., 2005). The PCC is given as (Hair et al., 2006);

$$\left[\frac{\text{Sum of correctly predicted outcomes in the diagonal matrix}}{\text{Total number of observations}} \right] \times 100 \quad (3.14)$$

In the literature, studies often compare their results to others for recognition and acceptance. However, one statistically based measure of predictive acceptance level is the Press's Q statistic (Hair et al., 2006). It is a statistical measure that compares the classification accuracy to a random process (chance) with a critical value of 6.63 at the 0.01 significance level (Hair et al., 2006). For the purpose of evaluating the acceptability of both the in-sample and out-sample predictive accuracies of the models in the study, their performances (both in-sample and out-sample) were subjected to this test (Press Q- test) as well as the chance criterion. Calculation of the Press Q- statistic and the proportional chance criterion are shown in equation 3.15 and 3.16 respectively.

$$\text{Press's Q} = \frac{[N - (nK)]^2}{N(K - 1)} \quad (3.15)$$

Where N is the total sample size; n is the number of observations correctly classified and K represents the number of groups. The chance criterion is as well written as;

$$C_{PRO} = [P^2 + (1 - P)^2] \quad (3.16)$$

Where C_{PRO} is the proportional chance criterion; P is the proportion of firms in groups 1 and $1 - P$ which stands for the proportion of firms in group two.

3.10 Specification Error Test

In practice, econometric models are in-exhaustive which often lead to specification error (Gujarati, 2004). Some of the common specification errors relate to the omission of relevant variable from the set of predictor variables in a regression equation and ,or misspecification of the functional form of the model (Koutsoyiannis, 2001; Hair et al., 2006).

In order to test whether the models have been correctly specified, the study utilised the “linktest” suggested by Pregibon (1979). The intuition behind the test is that, if the model is properly specified, then one should not be able to find any statistically significant additional predictor variable/s to the estimated model expect by chance. Let $Y = f(X\beta)$ be the new model and $\hat{\beta}$ be the parameter estimated. The linktest calculates $\delta = X\hat{\beta}$ and δ^2 as the predictors to rebuild the model. The model is then refitted with these two variables and the test is based on the outcome of δ^2 . The decision rule is such that, if the model is correctly specified, then, the variable δ should be a statistically significant predictor, since it is the predicted value from the model and δ^2 shouldn't have predictive power (i.e. insignificant) (Stata Corporation, 2009) Otherwise, it implies that relevant variable/s has/have been omitted from the model or the functional form of the model is incorrect.

3.11 Data Analysis

Quantitative data analysis is generally an organised and compressed assembly of information that permits conclusion drawing and also a way of providing information about variable as well as relationships between them by means of statistical methods and tools (Amaratunga et al., 2002).

By applying the logit and probit regression methods and with the aid of STATA 11. IC statistical

software, I was able to compute and display meaningful information which gave me the grounds to interpret the empirical results.

Pacitti (1998) cited in Amaratunga et al. (2002), outlines a quantitative data analysis plan that follows the following pattern:

- Raw data assessment;
- Data entry;
- Data processing;
- Communicating findings;
- Data interpretation and;
- Completing data analysis

In this study the steps outlined by Pacitti (1998) served as the guideline for our data analysis. First, the raw data was assessed for any discrepancies. After this process, relevant information from the financial statement of the respective firms was extracted to compute the accounting/financial ratios. This was undertaken with the help of Microsoft Excel. However, for us to process the data into meaningful statistical results, we employed the STATA 11 IC statistical package. At the fourth state of the data analysis procedure, I presented and simplified the results in the form of tables and through graphical representations for easy exposition. Finally, the empirical results were interpreted with reference to the tables and the figures in congruence with literature.

CHAPTER FOUR

DATA ANALYSIS

4.0 Introduction

This chapter of the study covers the presentation of empirical results and its statistical interpretation. It first delves into the descriptive statistics of the analysis followed by the correlation structure of the variables being used. The estimation results from the Logit and Probit models are also discussed.

4.1 Descriptive statistics and distribution of variables

Descriptive statistics is one of the key ways of assessing data prior to estimation or one of the preparatory works towards actual estimation of data. Table 4.1 below shows the descriptive statistics of our analysis in relation to the variables (financial ratios) being used. The Variable X_1 shows the ratio of earnings that a firm has to cover its interest expense. The mean value of 34.6436 shows that on the average, the companies forming the estimation have 34.6436 more earnings to cover their interest expense. It is also clear that at least one company has less cash to the tune of 456.25 to cover its interest expenses. We can say that such a company will have difficulties in settling its debt and therefore is highly risky. The maximum value of 634.2965 also indicates that at least one company has 634.2965 more earnings to cover any outstanding interest payment. On the whole, we can say that the companies perform well as far as their earnings to interest expense is concern.

The Total liabilities to total assets ratio also showed some good results for all the companies. We can observe that on average, the companies have 90.50% less liability to their total assets. Said differently, on average, the companies have 90.50% more assets to cover their liabilities. Variable X_3 (Cash to Total Assets ratio) also indicate that 13.70% of the company's assets are

made up of cash. This is good for firm's liquidity since debts are mostly paid with cash. It is clear as well that the mean value of X_4 (working capital to total assets ratio) is an indication that 24.59% of the assets form part of the working capital. This one's again boosts the liquidity of a firm.

The X_5 (Current Assets to Current Liabilities ratio) also showed impressive average score for the companies. The 11.1391 score means that on average, the companies have 11.1391 times more current assets in terms of value to cover their liabilities. The minimum value of .002496 is also a clear indication that some of the companies have very low assets in relation to their liabilities and vice-versa for the maximum average. It is also clear from the table that the x_6 variable (Earnings before interest and taxes to total assets ratio) of -1.4151 means that on average, the companies have 1.4151 times less earnings in relation to their total assets. Similarly, the -1.682713 average value for the X_7 (Retained earnings to total assets) ratio indicates that on a whole, the companies retain 1.6827 times less of their earnings in relation to their total assets. It can be observed though, that some of the companies have more retained earnings as evident from the maximum values. The companies also have 4.284 times more accounts receivable to their liabilities (X_8). They however have 81.57% less operating income to their total assets (X_9).

The descriptive results also showed that on the average, the companies have 31.77% less of current liabilities to total liabilities (X_{10}). Meaning in a whole, they are have more total liabilities which makes them less insolvent. It is also evident that the firms have 34.6554 times more earnings plus interest to interest (X_{11}). Meaning that, they have high earnings in general. Some of the firms though recorded some negative earnings indicating losses per the minimum value for

the ratio. The Net Current Assets ratio (X_{12}) indicates that on average, a company has 146803.2 more current assets than liabilities. This is also good for a company that needs to be solvent and remain credit worthy. We also found out that, the total liabilities to net current ratio (X_{13}) of 17.8231 gives us the indication that the companies have 17.8231 more liabilities in excess of their net current liabilities. The ratio of cash to current liabilities (X_{14}) indicates that on the average, a company has 3.1021 times more cash in relation to its current liabilities. This is good for the sake of credit worthiness since cash is needed to pay outstanding liabilities. The last variable (X_{15}) represents the total assets of the companies. This is being used as a proxy for company size. What the 435266.9 therefor means is that, on average, the size of a company is approximately 435267.

From this discussion, it can be seen that company characteristics are essential tools to assess the wellbeing of a company. This is evident from the performance of the companies (either good or bad) as far as the financial ratios are concern. It is thus, justifiable to have much financial variables for assessment whenever a credit worthiness evaluation is to be done.

Table 4.1: Descriptive Statistics

Variable	Obsevation	Mean	Std. Dev.	Min	Max
X_1 Earnings to Interest Expense ratio,	290	34.6436	123.9176	-456.2599	634.2965
X_2 Total liabilities to total assets ratio,	290	.9049998	.316968	.0192132	2.411802
X_3 Cash to Total assets,	290	.1370294	.1816986	.000077	.9761568
X_4 working capital/Total assets ratio,	290	.2459024	.507398	-2.529116	.9611042
X_5 Current assets to current liabilities,	290	11.13908	25.74819	.0024964	228.3692
X_6 Earnings before interest and tax to total asset ratio,	290	-1.415133	14.60616	-164.3558	18.94422

Table 4.1: Descriptive Statistics (continued)

Variable	Observations	Mean	Std. Dev.	Min.	Max.
X_7 , Retained earnings to total assets, assets	290	-1.682713	16.86449	-202.5748	22.96014
X_8 , accounts receivable to total liabilities, assets	290	4.283937	12.79837	.0013074	153.0403
X_9 , represents operating income to total assets,	290	-.8157572	15.35153	-167.722	19.69942
X_{10} , current liabilities to total liabilities	290	.3177127	.3774992	.001706	2.736895
X_{11} , Earnings plus interest to interest,	290	34.65544	123.9234	-456.2585	634.2965
X_{12} . net current assets ratio,	290	146803.2	700605.9	-1071638	6848183
X_{13} . total liabilities to net current ratio	290	17.82312	221.5671	-994.023	3456.285
X_{14} . cash to current liabilities,	290	3.102116	8.994643	.0004049	86.62711
X_{15} , represents total assets	290	435266.9	1208775	108.1348	9433396

4.2 Correlation Analysis and Variance Inflation Tests

Correlation analysis is one way of assessing the interrelation/interdependence of variables for an estimation procedure. This gives a clear relationship that exists between the variable prior to estimation. It also gives the relationship that exists between the dependent variable and each independent variable. One important significance of the correlation matrix is its ability to give a signal as to the level of multicollinearity that is to be expected between groups of variables.

From table 4.2 below, it is clear that all the independent variables have a negative relationship with the probability of default except X_2 , X_{10} , X_{12} , and X_{13} . Going through the inter-correlations between the variables, it can be observed that the correlations between most of the variables are quite low indicating that they will not pose any multicollinearity problems to us. However, looking at the correlation coefficients between: X_6 and X_7 (0.9879), X_6 and X_9 (0.9964), X_7 and X_9 (0.9887), X_{12} and X_{15} (0.8138), it is clearly indicative that these high inter-correlations between these variables will pose tremendous multicollinearity problems to us and if not checked, can lead to biased/unreliable estimates. Furthermore haven't said these, it is important to note that, one cannot judge or tell of the multicollinearity effect as a result of the high correlation coefficients by merely looking at them from their face value. It is therefore prudent to conduct a variance inflation factor (VIF) test to determine the extent of multicollinearity and which variable(s) is/are contributing to the problem.

Table 4.2: Correlation Analysis

probability of default	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂	X ₁₃	X ₁₄	X ₁₅	
-----+-----																
Probability 1.0000 of default																
X ₁	-0.1676	1.0000														
X ₂	0.0248	0.0001	1.0000													
X ₃	-0.1910	0.3419	-0.0070	1.0000												
X ₄	-0.2799	0.1481	-0.0748	0.1388	1.0000											
X ₅	-0.1224	0.1241	-0.1325	0.1086	0.3227	1.0000										
X ₆	-0.1223	0.3602	0.2435	0.0607	0.0138	0.0232	1.0000									
X ₇	-0.1292	0.3581	0.2483	0.0622	0.0102	0.0207	0.9879	1.0000								
X ₈	-0.0976	0.1534	-0.1603	0.0900	0.2510	0.5722	0.0322	0.0322	1.0000							
X ₉	-0.1260	0.3537	0.2480	0.0955	0.0084	0.0191	0.9964	0.9887	0.0380	1.0000						
X ₁₀	0.1030	-0.0811	-0.0929	-0.0370	-0.4682	-0.2257	-0.0907	-0.0770	-0.1539	-0.0809	1.0000					
X ₁₁	-0.1676	1.0000	-0.0000	0.3419	0.1481	0.1241	0.3602	0.3581	0.1534	0.3537	-0.0811	1.0000				
X ₁₂	0.0034	0.0770	0.0314	-0.0209	0.1641	0.0018	0.0210	0.0213	-0.0182	0.0152	-0.1100	0.0770	1.0000			
X ₁₃	0.0752	-0.0487	0.0208	-0.0482	-0.0330	-0.0276	0.0077	0.0078	-0.0183	0.0045	-0.0541	-0.0487	-0.0142	1.0000		
X ₁₄	-0.1259	0.1972	-0.0788	0.5578	0.2477	0.5691	0.0284	0.0271	0.3378	0.0396	-0.1980	0.1972	-0.0105	-0.0199	1.0000	
X ₁₅	-0.0017	0.1187	0.0728	-0.0704	0.0047	-0.0599	0.0360	0.0363	-0.0653	0.0269	-0.0853	0.1187	0.8138	-0.0083	-0.0537	1.0000

Source: Estimated Sample

X₁ stands for Earnings to Interest Expense ratio, X₂ is Total liabilities to total assets ratio, X₃ represents Cash/ Total assets ratio, X₄ represents Networking capital / Total assets ratio, X₅ represents Current assets to current liabilities, X₆ represents Earnings before interest and tax to total asset ratio, X₇ represents Retained earnings to total assets, X₈ represents accounts receivable to total liabilities, X₉ represents operating income to total assets, X₁₀ represents current liabilities to total liabilities, X₁₁ represents Earnings + interest to interest, X₁₂ represents the net current assets ratio, X₁₃ represents total liabilities to net current ratio, X₁₄ represents cash to current liabilities, X₁₅ represents total assets.

Table 4.3 below shows the results of the variance inflation factor test. The idea behind the VIF test is that, even though variables in any estimation will have the potential of inflating the variance of the estimation, it should not be so high to the extent that it will render the estimation invalid and unreliable. According to Hair et al. (2006), variables in any a reliable estimation result should not have a VIF of more than 10. Thus, the ability/tendency of an individual variable to inflate the variance of the estimation should not be more than 10. This translates to a tolerance level of 0.1 (i.e. Tolerance is given as: $1/VIF$). From the table, it is clear that five of the variables namely: X_{11} , X_1 , X_9 , X_6 , X_7 have VIF values above the recommended value given by Hair et al. (2006).

It can be recalled that these are the same variables that recorded high correlation values in the correlation matrix. To resolve this problem, variable x_{11} was first dropped from the list of variables for the estimation. It turned out that after the removal of x_1 from the model, the problem of multicollinearity still pertained. After the first removal, the test was conducted again. It further resulted that variables x_6 and x_9 had high VIF values above the recommended value of 10 hence, they were dropped as well. After dropping these variables, the remaining variable showed VIF values below 10 and so was the overall mean VIF. This therefore, means that out of the fifteen variables outline, only twelve were finally entered into the model for estimation.

Table 4.3: Variance Inflation Test Results

Before Variables removal			After Variables removal		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
X ₁₁	1.05e+07	0.000000	X ₁₅	3.2	0.304821
X ₁	1.05e+07	0.000000	X ₁₂	3.26	0.307012
X ₉	217.63	0.004595	X ₁₄	2.38	0.419550
X ₆	191.44	0.005224	X ₅	2.20	0.454885
X ₇	48.88	0.020460	X ₃	1.82	0.549115
X ₁₅	3.31	0.302494	X ₈	1.53	0.653096
X ₁₂	3.27	0.305955	X ₄	1.53	0.654810
X ₁₄	2.46	0.405831	X ₁	1.40	0.716642
X ₃	2.33	0.428544	X ₁₀	1.37	0.731597
X ₅	2.22	0.450213	X ₇	1.25	0.801953
X ₈	1.60	0.625384	X ₂	1.14	0.880284
X ₄	1.54	0.650248	X ₁₃	1.01	0.988566
X ₁₀	1.39	0.719437			
X ₂	1.20	0.831466			
X ₁₃	1.01	0.987542			
Mean VIF	1.40e+06		Mean VIF	1.85	

4.3 Analysis of Logit results

4.3.1 Interpretation of Estimated Parameters

Logistic regression is one of the widely used credit risk modeling techniques mainly because of its relative simplicity and rigidity to strict multivariate assumptions imposed on other models such as the linear regression model. In this study, it is used as a credit risk model to ascertain its classification ability and also to find the variables that can best contribute to its classification accuracy in relation to creditworthiness.

Table 4.4 below is a summary of the results of the logistic estimation. The table contains the final results of the estimation after five backward selection processes. Backward selection procedure is an estimation technique where all variables for estimation are entered into the model and then the most insignificant variable is removed and the model re-estimated until all variables in the model are significant at a given significance level. In our estimation, a variable was removed using the 0.10 and 0.05 significance levels. After the five backward elimination procedures, seven variables were retained in the final model because they met the 0.10 and 0.05 significance criterion. These include: X_2 , X_3 , X_5 , X_8 , X_{10} , X_{12} , and X_{15} . For the purpose of our discussion, the significant coefficients were transformed into actual probabilities (marginal probabilities) in order to make our discussion very simple and clear. The interpretations of the significant variables are therefore interpreted using the marginal probabilities:

Regarding the significance of X_2 , it means that all things being equal, a unit increase in the ratio will lead to a 23.51 percent reduction in probability of default. The X_3 ratio also indicates that a one-unit increase in the cash to total assets ratio will lead to a 0.0310 reduction in default probability *ceteris paribus*.

Following the same way the above variables have been interpreted, we can say that with the X_5 ratio, all things being equal, a unit increase in the ratio will result in a 17.25 percent reduction in the probability that a company will default on credit. Similarly, a 1-unit increase in the x_8 ratio will result in a 5.14 percent lower probability of a company defaulting.

Looking at table 4.4 once more, it is clear that all the variables have their unique magnitudes on default probability. The -0.1573 marginal probability of the X ratio indicates that ceteris paribus, a unit increase in the X_8 ratio will lead to a 15.73 percent lower probability of default. Significance of the X_{10} ratio at the 0.10 significance level and the .0804 marginal probability means that a unit increase in the ratio will result in a 8.04 percent increase in default probability.

The last statistically significant ratio under the logit estimation is the total assets ratio (X_{15}). This ratio was used as a measure of firm size and is significant at the 0.05 significance level. Still interpreting from the marginal probability perspective, we can say that the -0.1159 marginal probability associated with the X_{15} ratio signifies that a unit increase in the ratio will lead to a reduction in default probability by 11.59 percent all things held constant. This is an indication that bigger companies are less likely to default.

We can therefore write our final logit model as follows :

$$\ln \left(\frac{P(Y=1)}{1+P(Y=1)} \right) = 2.28476 - 1.30657X_2 - 0.17261X_3 - 0.95862X_5 - 0.28557X_8 - 0.87433X_{10} - 0.44656X_{12} - 0.64386X_{15}$$

Table 4.4 Estimated Logit Results

Variables	Coefficient.	Marginal Probabilities	Std. Err.	z	P> z	[95% Conf. Interval]
X ₂	-1.306572	-.2351308	.7248257	-1.80	0.071	-2.727204 .1140602
X ₃	-.1726062	-.0310622	.0847071	-2.04	0.042	-.338629 -.0065833
X ₅	-.9586189	-.1725131	.3934221	-2.44	0.015	-1.729712 -.1875257
X ₈	-.2855674	-.0513907	.1112693	-2.57	0.010	-.5036512 -.0674835
X ₁₀	-.8743381	-.1573459	.2861271	-3.06	0.002	-1.435137 -.3135393
X ₁₂	.4465609	.0803631	.244861	1.82	0.068	-.0333579 .9264797
X ₁₅	-.6438572	-.1158686	.2693237	-2.39	0.017	-1.171722 -.1159925
Constants	2.284761		1.265663	1.81	0.071	-.1958933 4.765415

4.3.2 Interpretation of Logit Model Statistics

Table 4.5 below summarizes the logistic statistical output in relation to the model. These statistics tell us about the general wellbeing of our estimated model. Similar to a linear Ordinary Least

Square regression model that assess the overall performance of the estimation using the R^2 , the logit mode uses the Pseudo R^2 . Like the OLS regression, the Pseudo R^2 in our case means that 10.2% of the variation in default is being explained by the independent variables. To assess the acceptability of this result, we conducted a goodness of fit test using the Homer and Lemenshow test. The null hypothesis in this test is that “the model fit is acceptable”. After conducting this test, we failed to reject the null hypothesis at the 0.05 significance level (see table 4.5) and therefore conclude that our logit model is fit. One other model fit diagnosis is the Likelihood ratio (LR) test. This statistic is also similar to the F-test in OLS regression. From table 5, the LR ratio is 29.94 with a probability value of 0.0001. This means that all our estimated variables together, are statistically significant at the 0.001 significance level. it is evident that ,

Table 4.5: Logit Model Statistics

Model Statistics		Goodness of Fit Test	
LR	29.94 (0.0001)	Pearson χ^2	264.46 (0.0645)
Pseudo R^2	0.1026		

Note: Values in parenthesis are probabilities

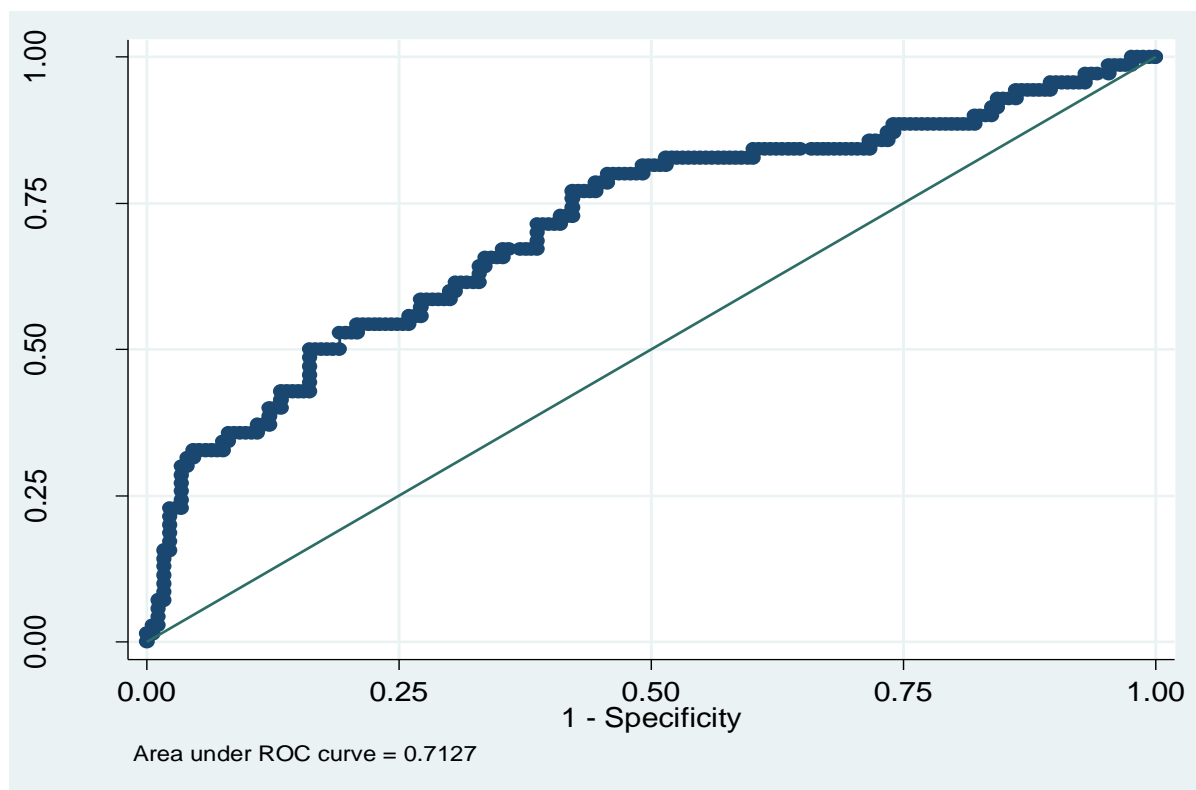
4.3.3 Classification Accuracy of the Logit Model

The classification accuracy of a model is an intuitive way to determine the overall predictive performance of the model. In this study, the logit model is tested on this premise to ascertain its

in-sample predictive accuracy. To do this, we used the Percentage Correctly Classified (PCC) and Receiver Operating Characteristic (ROC) Curve. This produces the Area Under the Curve (AUC). It must be stated here that these two forms of model performance assessment (i.e. PCC and AUC) are similar in the sense that they both give the same meaning to the situation at hand just that they operate under different criteria.

From table 4.6 below, it can be observed that the overall predictive accuracy or PCC of the logit model is 77.37 percent. Meaning that, the model has a 77.37 chance of correctly classifying both companies that are likely to default and those who will not. We can say that though the model hasn't achieved 100 percent predictive accuracy, its performance rate of 77.37 percent can be described as good.

As indicated above, the AUC is another way of determining the predictive power of a model. From figure 1 below, we can observe that the AUC is 0.7127. Similar to the PCC, it indicates that, the model has the probability of correctly classifying good and bad borrowers.

Figure 4.1: ROC curve for Logit Model**Table 4.6: Predictive Accuracy of the Logit Model**

PCC (%)	AUC (%)
77.37	71.27

4.4 Analysis of Probit results

4.4.1 Interpretation of Estimated Parameters

The Probit model is similar to the logit. Their similarity is high in that, most often than not, the two models produce more or less the same results, even they do differ in certain aspects. In our study, the result of the probit model is similar to that of the logit though there are slight differences. In this respect, we shall go on with the interpretation of the probit results as we did for the logit model. It must be indicated here that the same number and category of variables were statistically significant in the probit model as it was in the logit model after five backward stepwise selection procedures. Table 4.7 shows the statistically significant results of the probit estimation at the 0.10 and 0.05 significance levels.

From the table, it is clearly visible that the variables that were significant under the logit model are the same statistically significant ones under the probit model. Looking at the x_2 variable, we can say that an ith -unit increase in the ratio will lead to a 23.49 percent reduction in the probability of default. The x_3 result also means that a unit increase in the ratio will cause a 0.0337 decrease in default probability. Similarly, a unit increase in x_5 will lead to a 15.86 percent decrease in the probability of a company defaulting.

In the same vein as the other variables, a unit increase in x_8 , x_{10} , and x_{10} will result in a 15.46 percent, 47.75 percent, and 34.79 percent reduction in the probability of a company to default respectively all things being equal. Also, *ceteris paribus*, a unit increase in the x_{12} ratio will lead to a 0.2396 increase in the probability of a company defaulting.

We can write our empirical probit model as follows:

$$\Phi^{-1}(P(Y = 1)) = -0.7640432X_2 - 0.109616X_3 - 0.5157922X_5 - 0.1546445X_8 - 0.477476X_{10} \\ + 0.239558X_{12} - 0.3478844X_{15}$$

Table 4.7: Estimated Probit Results

Variables	Coefficient.	Marginal effects	Std. Err.	Z	P> z	[95% Conf. Interval]
x ₂	-.7640432	-.2348944	.4342519	-1.76	0.079	-1.615161 .0870749
x ₃	-.1096916	-.0337231	.0507733	-2.16	0.031	-.2092054 -.0101777
x ₅	-.5157922	-.1585731	.2205381	-2.34	0.019	-.9480389 -.0835456
x ₈	-.1546445	-.0475433	.0646486	-2.39	0.017	-.2813535 -.0279355
x ₁₀	-.477476	-.1467933	.1583627	-3.02	0.003	-.7878611 -.1670909
x ₁₂	.239558	.0736488	.1391956	1.72	0.085	-.0332603 .5123763
x ₁₅	-.3478844	-.1069522	.1515683	-2.30	0.022	-.6449528 -.050816
Cons	1.188029		.7412604	1.60	0.109	-.2648143 2.640873

4.4.2 Interpretation of Probit Model Statistics

The table below presents the results of the probit model statistics. As indicated earlier, the interpretation of the probit results is the same as the logit. The results of the estimation show that the probit model has a LR of 28.94. This value is statistically significant at the 1 percent alpha level as shown by the p-value of 0.0001. This means that all the variables in the probit model are

together, statistically significant. The Pseudo R^2 of the model also indicates that just 9 percent of the variation in default probability is being explained by the independent variables. Therefore, to statistically test the significance of this result, we performed a goodness of fit test using the Hosmer and Lemeshow statistic. The null hypothesis of "...the model fit is acceptable..." is tested in this case. The results of the test as shown in table 4.8 indicates that we can fail to reject the null hypothesis at the 0.005 significance level and conclude that the model fit is statistically acceptable.

Table 4.8: Probit Model Statistics

Model Statistics		Goodness of Fit Test	
LR	28.94 (0.0001)	Pearson χ^2	260.31 (0.0900)
Pseudo R^2	0.0992		

Note: Values in parenthesis are probabilities

4.4.3 Classification Accuracy of the Probit Model

In order to establish the in-sample predictive power of the probit model, we calculated the PCC and the AUC. From table 4.9, the PCC of the probit model is 76.95%. This indicates that the model could correctly predict 76.95 percent of all the cases in the sample which is quite good.

The AUC also shows that the model can correctly predict 71.18 percent of the in-sample companies. This is shown graphically in figure 2 below.

Figure 4.2: ROC curve for Probit Model

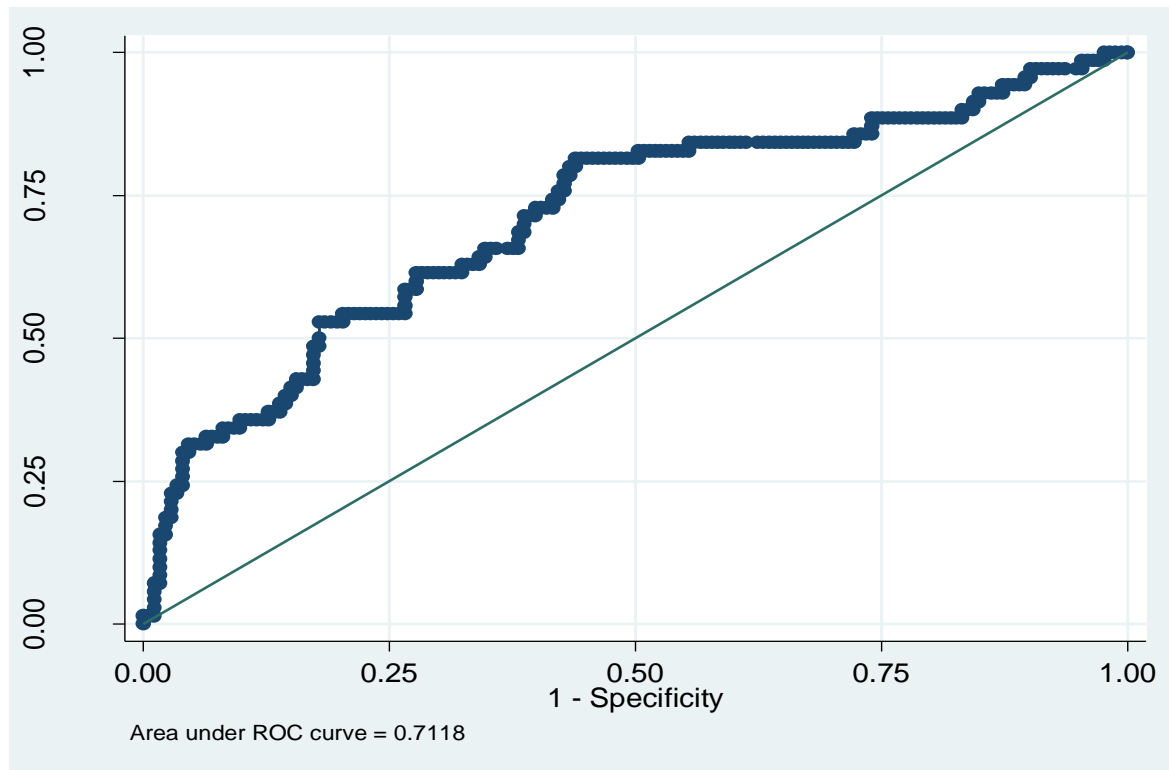


Table 4.9: Predictive Accuracy of the Probit Model

PCC (%)	AUC (%)
76.95%	71.27

4.5 Validation Results

The purpose of validating a model is to get a fair idea of how the model will perform when it's applied to a sample outside the training sample. In the case of this study, the models were validated using a holdout sample of 85 observations. The result of both the logit and the probit is shown in table 4.10 below. At the end of the validation, it was found that the external predictive power of the logit model is 54.12 percent and that of the probit is 52.94 percent. The levels of the accuracy rates are not so surprising given the in-sample performance of the models. It can be argued though that, a relatively lower in-sample performance does not result entirely into a lower out-of-sample performance. However, give a relatively lower in-sample performance, an equally lower out-o-sample performance can be expected though it is not and should not always be the case. The relatively lower out-sample performance of the models are also evident from the relatively high type I and type II error rates of the models.

Table 4.10: Validation Results

Logit Model			Probit Model		
PCC (%)	Type I Error (%)	Type II Error (%)	PCC (%)	Type I Error (%)	Type II Error (%)
54.12	55.17	41.07	52.94	55.17	42.86

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter presents a summary of the findings from the study as well as conclusions, recommendations and areas for future research.

Credit risk management has become a key component of banking business more so following the recent financial meltdown. With the growing credit industry and the ensuing risk associated with it, financial institutions are finding prudent ways to identify assess measure and monitor the risk profile of borrowers as well as the enterprise risk of the organization in general. In this study, the background to credit assessment was looked at. The chapter also makes recommendations based on the empirical evidences from the research result to guide policy formulation and for further research.

5.1 Summary

Following the ensuing consequences of the credit crisis, and the search for more stringent statistically based credit screening tools to aid in the credit granting process, banks mostly in the advanced world have become more sophisticated by relying on statistical tools to guide their credit decisions. This study set out to model credit risk by using the logit and the probit regression models and also to compare their performance in terms of predictive power. These two models were settled upon after thorough review of the credit scoring literature. Literature was reviewed on the concepts of credit risk assessment and risk management. As indicated, the study employed two binary choice models namely: logit and probit models. These were used to model the credit risk of the firms involved. The result of the research shows that both models are

good for credit scoring. Specifically, the logit model appears to be a better predictor of credit risk as compared to the probit model.

5.2 Conclusion

Credit risk management has become a key component of banking business more so following the recent financial meltdown. With the growing credit industry and the ensuing risk associated with it, financial institutions are finding prudent ways to identify, assess, measure and monitor the risk profile of borrowers as well as the enterprise risk of the organization in general. In this study, the background to credit risk management was looked at.

One of the objectives of the thesis was to build models that can be used to ascertain the credit worthiness of borrowers. In addition we purposed to compare the predictive accuracy of the models we purposed to use. To achieve these, we employed the logit and the probit regression models. After our estimation procedure, using the backward selection technique, we found that both models had the same set of significant variables/ratios. These are the: total liabilities to total assets ratio; cash to total assets ratio; current assets to current liabilities ratio; accounts receivables to liabilities ratio; current liabilities to total liabilities ratio; the net current assets ratio; and finally the total assets variable as a proxy for firm size.

On the case of model fit, all the two models were found to be statistically acceptable per the results of the Hosmer and Lemeshow goodness of fit test. Considering the predictive performance/ability of the models using the percentage correctly classified rate and area under the receiver operating characteristic curve, we found that though the logit model has a relative highly predictive accuracy both in-sample and out-sample, the difference does not appear to be

large enough to warrant any significant difference. However, due to the fact even a fraction of an improvement of a credit risk model can prove to be useful, we can say that the logit model appear to be slightly ahead of the probit model in terms of both in-sample and out-sample performance.

5.3 Recommendations

Future related works can compare more statistical models in addition to the ones used in this thesis to determine their capabilities as well.

The outcome of this study can be useful to both academia and industry. Academic wise, it will greatly contribute to the credit assessment and credit risk management literature from the Ghanaian perspective.

In terms of its contribution to industry, lending institutions can apply such a model to curtail the use of the traditional means of creditworthy assessment and enjoy the benefits associated with credit scoring, we advise that the institutions makes use of the logit model in scoring and ascertaining the risk level of borrowing firms.

This is due to the fact that the logit model has a better chance of capturing unworthy credit applicants and at the same time, be able to predict creditworthy ones thereby reducing non-performing loans and increase profits during credit assessment and granting process.

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APPENDIX A

INDEPENDENT VARIABLES(FINANCIAL RATIOS)

PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	627.0432	0.931221	0.49076	0.171017	4.730331	0.997815	0.973469	0.144912551
1	-1.69371	0.931217	0.028501	-0.12968	2.53359	-0.18027	-0.24087	0.210364961
0	0.534216	0.931217	0.110018	0.501567	9.772458	0.020826	0.017384	6.186558436
0	8.824488	0.931215	0.009171	0.198016	4.622263	0.132813	0.09366	4.861145677
1	-2.44258	0.931217	0.283848	0.23172	5.44381	-0.02465	-0.03294	2.530170326
0	209.3177	0.931217	0.006775	0.715193	18.81331	0.056265	0.056253	11.41790585
0	135.232	0.931217	0.183965	0.136473	4.064969	0.164586	0.180313	2.006989203
0	13.6417	0.931216	0.039471	0.639618	27.04351	0.01816	0.026046	1.806706069
0	6.352948	1.1667	0.521553	-0.32663	1.903167	0.424579	3.118725	0.206005952
1	-1.56937	0.931217	0.028501	-0.12968	2.53359	-0.18027	-0.24087	0.210364961
0	1.57194	0.931217	0.000477	-0.14029	1.565172	0.023033	0.011176	0.031944295
0	6.429993	0.931217	0.137402	0.665784	27.84237	0.044608	0.042471	8.456356497
0	2.044482	0.931217	0.224276	0.033274	3.020394	0.058035	0.060956	0.390855199
1	-0.1826	0.931217	0.085635	0.119379	3.326276	-0.02563	0.153519	0.88456898
1	-5.68508	0.931217	0.047992	-1.03216	1.284303	-0.51746	-0.81319	0.325419449
0	9.142288	0.931217	0.027754	0.72515	12.19908	0.098637	0.079953	12.69394562
0	13.51581	0.931211	0.006125	-0.00442	2.862007	0.111449	0.11139	3.008782297
0	3.408866	0.931217	0.02452	0.03078	3.002356	0.028246	0.025294	0.786836663
0	82.80767	1.023152	0.327218	0.344875	5.010174	0.110515	0.103634	2.711158425
0	0.46185	0.931217	0.058072	0.560271	14.744	0.028432	0.021859	6.589066001
0	-58.0094	0.931162	8.54E-05	-0.04114	0.009109	-0.05138	-0.06984	0.004126469
1	282.4061	0.959609	0.505721	0.17623	4.730331	1.026238	1.003146	0.144912551
0	8.976017	0.931217	0.000139	0.016004	3.219076	0.220101	0.009098	2.69591023
1	-0.34605	0.931217	0.038748	0.069386	3.149682	-0.00219	-0.00351	0.263484033
0	1.880569	0.931217	0.02452	0.03078	3.002356	0.028246	0.025294	0.786836663
0	5.473034	0.930807	0.000475	0.053655	3.154171	0.242492	0.201141	0.063922392
0	15.1434	0.931217	0.324988	0.226141	5.215709	0.102633	0.109494	2.182379713
0	5.584676	0.931217	0.164686	0.475824	21.36211	0.03223	0.04533	12.0162589
1	-54.398	0.931218	0.002703	0.000438	3.071305	-0.01797	-0.0275	2.285240398
0	1.897566	0.931217	0.02357	0.664277	25.20481	0.002548	0.005202	0.481946371
0	2.083884	0.931217	0.113648	0.693462	29.02001	0.016116	0.007521	10.31877902
0	2.493704	0.931221	0.071558	0.933175	153.4111	0.015842	0.009503	153.0402899
0	3.740655	0.931217	0.726623	0.571105	28.75866	0.085475	0.031259	60.76098236
1	11.59481	0.931217	9.87E-05	0.142744	4.759139	0.407729	-0.06859	4.408398109
0	97.46049	0.931217	0.546648	0.347625	5.168393	0.108194	0.107634	1.607838788
0	12.57535	0.931217	0.049015	0.803602	18.68557	0.150908	0.129916	19.05373678
1	-4.35898	0.931217	0.000312	-0.107	0.007372	-0.02604	-0.04279	0.013189985
1	-1.99766	0.931215	0.077829	-0.00982	2.867924	-0.30513	-0.20339	0.856965415
1	-43.289	0.931233	0.028839	-0.03979	2.135222	-0.37265	-0.50946	1.546135747
0	2.532031	0.931217	0.922241	0.772818	70.20025	0.068518	0.017242	12.16631698

0	2.689087	0.931217	0.139434	0.24315	4.505242	0.004464	-0.00073	2.964755558
1	-8.01469	0.931217	0.172996	-2.48606	0.316755	-0.84773	-0.99126	0.02803659
0	26.95002	0.931217	0.067183	0.649024	58.08008	0.026067	0.036125	0.591214722
1	-1.19729	0.931217	0.005211	-0.22048	2.31711	-0.10061	-0.24685	0.179611152
0	426.5257	0.931217	0.348456	0.474399	40.71499	0.219374	0.043455	14.67687413
0	18.95904	0.931217	0.006077	0.028039	19.26124	0.008397	-0.00053	17.2570707
1	-7.27857	0.931217	0.172996	-2.48606	0.316755	-0.76987	-0.99126	0.02803659
0	51.77082	0.931217	0.067233	0.532092	7.16262	0.008817	0.009948	1.524982481
0	9.324368	0.931217	0.216441	-0.47124	1.07442	0.159637	0.091129	0.28805271
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
1	-94.6181	0.931232	0.010015	-0.03208	1.97959	-0.68196	-0.92088	1.465875583
0	146.7936	0.931217	0.133657	0.556332	7.343799	0.013822	0.014705	1.647251385
1	-1.21546	0.931217	0.001056	-0.25334	0.95682	-0.07698	-0.18759	0.224003811
1	-20.6105	0.931217	0.00023	-0.00089	2.59042	-0.00806	-0.01732	2.691572307
0	-1.5386	0.931217	0.000391	-0.20292	1.098014	-0.03496	-0.16526	0.232814708
0	169.6652	0.931217	0.364651	0.491993	54.55839	0.125906	0.061024	17.04288556
1	-16.9764	0.931217	0.118076	0.683327	19.08222	-0.98925	-1.32184	0.24015737
0	-0.32543	0.931217	0.057149	0.318331	6.615006	-0.00397	-0.01305	0.057729133
0	60.37942	0.931219	0.322131	0.060965	3.320231	0.045449	0.051618	1.179253363
0	-0.31296	0.931217	0.045156	0.308711	5.442144	-0.00308	-0.00411	0.0174206
1	-20.1609	0.931217	0.040109	0.427405	6.096652	-0.03878	-0.07135	0.349201216
0	1.574201	0.931236	0.236784	0.09795	4.591738	0.033167	0.033238	5.479601482
1	-4.99443	0.93124	0.099352	-0.12511	1.974057	-0.2032	-0.27151	1.696173844
0	137.824	0.931217	0.017387	0.763338	19.69827	0.151666	0.152729	9.294808215
0	264.9899	0.931217	0.089389	0.741708	18.98256	0.311833	0.307695	9.511644895
0	13.94812	0.80412	0.02324	0.82133	9.242504	0.438157	0.026055	4.234858077
0	-3.85225	0.368566	0.001601	-0.36549	0.084412	-0.05314	-0.08946	0.078627206
1	-0.98823	0.931217	0.014584	0.004165	3.023305	-0.0592	-0.09146	2.251253337
0	377.4276	0.033884	0.342138	0.912493	79.32149	0.515014	0.664805	56.40770958
1	-12.2769	0.868527	0.244323	0.576953	29.01582	-0.03192	-0.04265	13.45826936
0	0.374874	2.183631	0.003195	0.797544	3.935028	0.045538	0.152034	0.069382368
0	-5.48807	0.931217	0.002541	-0.12332	1.52217	-0.04636	-0.07325	0.241512196
0	2.309761	0.063123	0.01387	0.006583	3.377679	0.025672	0.005843	2.1975605
0	11.29241	0.058229	0.635744	0.653558	34.75018	0.570925	0.591622	0.309507246
1	-4.50806	0.931217	0.002754	-0.03761	1.771135	-0.04825	-0.07878	1.755185886
0	59.73817	0.041585	0.014806	0.23	18.59428	17.51287	22.96014	0.798746218
0	18.28454	0.78367	0.083587	0.800442	11.27256	0.383668	0.023485	3.919761916
1	-5.73762	0.931217	0.003047	-0.08951	1.749826	-0.07061	-0.11081	0.294793563
0	26.38204	0.863264	0.107439	0.634308	29.38804	0.071383	0.077289	2.154374856
0	4.744104	0.019213	0.012528	0.383009	59.46952	0.411781	0.552394	61.77449402
0	6.251048	0.485247	0.351931	0.26734	4.958388	0.182844	0.185243	2.18531871
0	124.331	0.931217	0.627677	0.227491	4.286732	0.174025	0.187543	0.878863842
0	-39.1713	0.703238	0.091568	0.017698	3.118847	-0.27983	-0.37391	1.643817578

0	16.33422	0.553704	0.325845	0.322547	5.618006	0.347466	0.369584	3.01437065
1	-15.2096	0.931217	0.250526	0.762471	126.4881	-0.02627	-0.0351	45.28705237
0	3.400271	0.083527	0.069106	0.31479	13.59345	3.67822	1.384208	0.708747855
0	-0.33042	0.659826	0.030803	0.94474	6.961744	-0.04836	0.079736	2.674635863
0	0.551771	1.69512	0.130767	0.839025	4.30317	0.053357	0.127953	0.094506925
0	5.772964	0.061428	0.007289	0.009981	3.800307	0.053725	0.060542	3.443294316
0	373.8826	0.931217	0.647619	0.827504	88.65079	0.528194	0.529397	16.58520132
0	40.39145	0.931217	0.045764	0.607729	228.3692	0.032502	0.044505	12.04155724
0	540.2308	0.024754	0.021388	0.564009	67.55779	0.88257	1.182738	67.84053858
0	25.78307	0.842461	0.246078	0.860491	7.998636	0.546965	0.070618	2.278902843
0	209.1651	0.931217	0.1445	0.79257	25.73761	0.357977	0.348453	16.88278154
0	0.145502	0.158021	0.193345	0.81443	17.52444	0.005037	0.041901	0.295097943
1	-20.4443	0.675193	0.002014	-0.02268	2.542308	-0.13525	-0.18072	0.809058204
0	28.94884	0.82463	0.232837	0.842278	6.375215	0.673136	0.03277	1.858668508
0	-7.45025	0.909635	0.071475	0.220984	31.95642	-0.04444	-0.07406	17.27469261
1	-23.1366	1.277829	0.039041	0.289968	3.542516	-0.90408	-1.26031	0.07062319
1	-96.4797	0.592056	0.01189	-0.15588	1.206277	-0.13664	-0.18258	0.206913942
0	14.25601	0.931217	0.092381	0.587537	87.55696	0.014717	0.021045	4.624036949
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	10.61058	0.931217	0.359779	0.151815	3.952043	0.069939	0.040619	1.542094397
0	32.06132	0.805402	0.188627	0.822639	14.11194	0.281003	0.012107	2.605957949
1	-28.9998	1.237495	0.006254	-0.18196	1.595202	-0.26947	-0.36007	0.446286085
0	-73.5074	0.931217	0.018672	0.009458	6.893663	-0.02046	-0.03079	6.64980093
1	-5.58755	1.566254	0.00742	-0.49626	0.639568	-0.40793	-0.54508	0.326545543
1	-0.15188	1.5107	0.050949	0.880565	4.552673	-0.02888	0.136974	1.840868697
0	-4.23936	0.931217	0.023373	0.131951	3.383106	-0.55821	-0.56975	1.76973043
0	22.12458	0.860856	0.068543	0.87928	5.958686	0.468735	0.070147	3.8060576
1	-456.26	0.133413	0.034087	0.205697	7.273917	-151.938	-202.575	0.581503145
0	0.741074	0.098562	0.036197	0.789877	25.6409	0.021694	0.052751	0.477669095
0	2.538403	0.931217	0.241987	0.124546	7.049598	0.016404	-0.0047	7.462222274
1	-32.9782	0.339703	0.163868	0.683721	8.610221	-0.41099	-1.25002	0.075294387
0	7.786157	0.878809	0.023449	0.116989	9.233317	0.077533	0.021364	8.674288906
1	-6.85522	1.122075	0.003021	-0.31776	0.846214	-0.44021	-0.58821	0.391100957
0	28.70348	0.789275	0.086429	0.806166	222.7305	0.178582	-0.118	13.81479693
1	-177.188	0.06054	0.048091	0.25623	14.9094	-72.5212	-96.3558	1.548618145
1	-0.83743	0.931217	0.005503	0.531601	6.715254	-0.16745	0.034212	2.692946143
0	156.2782	0.931217	0.10982	0.550682	7.409239	0.019368	0.019822	1.822752928
0	54.29629	0.931217	0.088081	0.527921	7.207881	0.023207	0.022876	2.205764318
0	627.436	0.931217	0.246626	-0.14164	1.960032	0.281985	0.314973	0.508691062
0	2.832145	0.931217	0.288185	0.113684	3.725338	0.039904	0.046997	1.775550273
0	-1.67763	0.931216	0.057886	0.32588	20.17417	-0.02891	-0.03861	0.389782546
0	117.5706	0.931217	0.188174	-0.21303	1.671058	0.211771	0.226469	0.698182304
1	-2.60161	0.931217	0.002726	0.254647	15.51532	-0.02277	-0.03043	0.166028674

0	-28.9982	0.931217	0.077976	-0.34769	1.073332	0.266203	0.271687	0.703521042
1	588.3856	1.028525	0.519451	0.173979	1.601953	1.079368	0.773628	0.045914481
0	-1.58929	1.028521	0.030167	-0.13192	0.858015	-0.195	-0.19143	0.066652598
0	0.501281	1.028521	0.11645	0.510254	3.309498	0.022528	0.013815	1.960165745
1	8.280453	1.028519	0.009707	0.201446	1.565355	0.143668	0.074433	1.540218417
0	-2.292	1.028521	0.300443	0.235733	1.843577	-0.02667	-0.02618	0.801665943
1	196.4131	1.028521	0.007171	0.727581	6.371233	0.060863	0.044705	3.617679872
0	126.8949	1.028521	0.19472	0.138837	1.376625	0.178038	0.143297	0.635899835
0	12.80068	1.02852	0.041779	0.650697	9.158438	0.019644	0.020699	0.57244159
1	5.961284	1.28861	0.552044	-0.33229	0.644518	0.459281	2.478488	0.065271478
0	-1.47262	1.028521	0.030167	-0.13192	0.858015	-0.195	-0.19143	0.066652598
1	1.475028	1.028521	0.000505	-0.14272	0.530054	0.024915	0.008882	0.010121316
0	6.033579	1.028521	0.145435	0.677316	9.428975	0.048254	0.033752	2.679334642
0	1.918438	1.028521	0.237387	0.03385	1.022873	0.062778	0.048442	0.123839608
0	-0.17134	1.028521	0.090641	0.121447	1.126462	-0.02773	0.122004	0.280269205
1	-5.33459	1.028521	0.050797	-1.05004	0.434937	-0.55975	-0.64625	0.10310677
0	8.57866	1.028521	0.029376	0.73771	4.131286	0.106699	0.06354	4.02198373
1	12.68255	1.028514	0.006483	-0.0045	0.969235	0.120558	0.088523	0.953310642
0	3.198707	1.028521	0.025953	0.031313	1.016765	0.030554	0.020101	0.249303436
0	77.70252	1.130062	0.346348	0.350848	1.696724	0.119547	0.082359	0.859010697
1	0.433377	1.028521	0.061467	0.569975	4.99314	0.030756	0.017372	2.08769732
0	-54.4331	1.028461	9.04E-05	-0.04185	0.003085	-0.05558	-0.0555	0.001307441
0	264.9956	1.05988	0.535286	0.179283	1.601953	1.110114	0.797212	0.045914481
0	8.422639	1.028521	0.000147	0.016282	1.090158	0.23809	0.007231	0.854179418
1	-0.32471	1.028521	0.041013	0.070587	1.066657	-0.00237	-0.00279	0.083482987
0	1.764631	1.028521	0.025953	0.031313	1.016765	0.030554	0.020101	0.249303436
1	5.135618	1.028069	0.000502	0.054585	1.068178	0.262311	0.159849	0.020253342
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	14.2098	1.028521	0.343987	0.230058	1.766329	0.111021	0.087016	0.691471034
0	5.240377	1.028521	0.174314	0.484065	7.2344	0.034864	0.036024	3.807263656
1	-51.0443	1.028523	0.002861	0.000446	1.040115	-0.01944	-0.02185	0.724061688
0	1.780579	1.028521	0.024948	0.675783	8.53575	0.002757	0.004134	0.152701179
1	1.955411	1.028521	0.120292	0.705473	9.827791	0.017433	0.005977	3.269429581
0	2.339966	1.028525	0.075741	0.949339	51.95354	0.017137	0.007552	48.48969536
1	3.510041	1.028521	0.769103	0.580997	9.739284	0.092461	0.024842	19.25167239
0	10.87998	1.028521	0.000105	0.145217	1.611709	0.441053	-0.05451	1.396768664
0	91.45199	1.028521	0.578606	0.353646	1.750305	0.117037	0.085538	0.509431948
0	11.80007	1.028521	0.05188	0.817521	6.327974	0.163242	0.103246	6.037036995
1	-4.09025	1.028521	0.00033	-0.10885	0.002496	-0.02817	-0.03401	0.00417915
0	-1.8745	1.028519	0.082378	-0.00999	0.971239	-0.33007	-0.16164	0.271523217
1	-40.6202	1.028539	0.030525	-0.04048	0.723105	-0.40311	-0.40487	0.489881791
0	2.375929	1.028521	0.976157	0.786203	23.77371	0.074118	0.013702	3.854808458
0	2.523303	1.028521	0.147585	0.247361	1.525726	0.004829	-0.00058	0.939361092

1	-7.52057	1.028521	0.18311	-2.52912	0.107271	-0.91702	-0.78777	0.008883188
0	25.28853	1.028521	0.071111	0.660265	19.66915	0.028197	0.028709	0.187322056
1	-1.12348	1.028521	0.005516	-0.2243	0.784702	-0.10884	-0.19617	0.056908479
0	400.2301	1.028521	0.368827	0.482617	13.78836	0.237304	0.034535	4.65026011
1	17.7902	1.028521	0.006433	0.028524	6.522926	0.009084	-0.00042	5.467776502
1	-6.82984	1.028521	0.18311	-2.52912	0.107271	-0.8328	-0.78777	0.008883188
1	48.57912	1.028521	0.071163	0.541309	2.425662	0.009537	0.007906	0.483179534
0	8.749515	1.028521	0.229094	-0.4794	0.363858	0.172685	0.072421	0.091267392
0	-88.7848	1.028538	0.010601	-0.03264	0.670399	-0.7377	-0.73184	0.464451946
1	137.7437	1.028521	0.141471	0.565968	2.487019	0.014952	0.011686	0.521919541
0	-1.14053	1.028521	0.001118	-0.25772	0.324032	-0.08327	-0.14908	0.070973968
1	-19.3399	1.028521	0.000244	-0.0009	0.87726	-0.00871	-0.01377	0.852804979
0	-1.44374	1.028521	0.000414	-0.20644	0.371849	-0.03782	-0.13134	0.073765636
1	159.2053	1.028521	0.385969	0.500515	18.47651	0.136196	0.048496	5.399913507
0	-15.9298	1.028521	0.124979	0.695163	6.462301	-1.0701	-1.05048	0.076092104
0	-0.30537	1.028521	0.06049	0.323845	2.240209	-0.0043	-0.01037	0.018291053
0	56.65698	1.028523	0.340963	0.062021	1.124415	0.049163	0.041021	0.373637794
1	-0.29366	1.028521	0.047795	0.314059	1.843013	-0.00333	-0.00327	0.00551959
0	-18.918	1.028521	0.042454	0.434808	2.064666	-0.04195	-0.0567	0.110641849
0	1.477151	1.028542	0.250627	0.099647	1.555018	0.035878	0.026415	1.73617161
0	-4.68652	1.028547	0.10516	-0.12728	0.668526	-0.2198	-0.21577	0.537420264
1	129.327	1.028521	0.018403	0.77656	6.67093	0.164062	0.121375	2.94499193
0	248.6531	1.028521	0.094614	0.754556	6.428552	0.33732	0.244529	3.013695044
0	13.08821	0.888144	0.024599	0.835556	3.130026	0.473969	0.020706	1.341783776
0	-3.61475	0.407079	0.001695	-0.37182	0.028587	-0.05748	-0.07109	0.024912454
0	-0.9273	1.028521	0.015437	0.004237	1.023859	-0.06404	-0.07268	0.713293137
0	354.1589	0.037424	0.36214	0.928298	26.86267	0.557107	0.528329	17.87236979
0	-11.52	0.959281	0.258607	0.586946	9.826371	-0.03452	-0.03389	4.264154112
0	0.351763	2.411802	0.003381	0.811359	1.33262	0.04926	0.120823	0.021983295
1	-5.14973	1.028521	0.00269	-0.12546	0.515491	-0.05015	-0.05822	0.076521371
0	2.167363	0.069719	0.01468	0.006697	1.14387	0.02777	0.004643	0.696280955
0	10.59622	0.064313	0.67291	0.664878	11.76834	0.617588	0.470169	0.098065105
0	-4.23014	1.028521	0.002915	-0.03826	0.599805	-0.05219	-0.06261	0.556117797
1	56.05527	0.04593	0.015671	0.233984	6.297058	18.94422	18.2467	0.253076891
1	17.15728	0.865557	0.088474	0.814306	3.817515	0.415026	0.018664	1.241947864
0	-5.38389	1.028521	0.003225	-0.09106	0.592588	-0.07638	-0.08806	0.093403182
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	24.75557	0.953467	0.113721	0.645295	9.952426	0.077217	0.061423	0.6825979
1	4.451627	0.021221	0.013261	0.389643	20.13969	0.445436	0.438994	19.57279614
0	5.865667	0.535951	0.372505	0.271971	1.679186	0.197789	0.147215	0.692402233
0	116.6659	1.028521	0.664373	0.231431	1.451726	0.188248	0.149043	0.278461574
1	-36.7564	0.77672	0.096921	0.018004	1.056215	-0.3027	-0.29715	0.520831564
0	15.3272	0.611562	0.344895	0.328134	1.902569	0.375865	0.293713	0.955081271

0	-14.2719	1.028521	0.265172	0.775678	42.83589	-0.02841	-0.02789	14.34887097
1	3.190642	0.092255	0.073146	0.320242	4.603497	3.978846	1.100047	0.224561569
0	-0.31005	0.728772	0.032603	0.961104	2.357634	-0.05231	0.063367	0.84743879
0	0.517754	1.872245	0.138412	0.853557	1.457293	0.057718	0.101685	0.029943827
0	5.417057	0.067846	0.007715	0.010154	1.286996	0.058116	0.048113	1.090982594
0	350.8325	1.028521	0.68548	0.841837	30.02209	0.571364	0.420719	5.254899609
1	37.90129	1.028521	0.048439	0.618255	77.33853	0.035158	0.035369	3.815279247
0	506.9252	0.02734	0.022638	0.573778	22.87883	0.954703	0.939936	21.49477795
0	24.19352	0.930491	0.260464	0.875395	2.708783	0.591669	0.056121	0.722053681
0	196.27	1.028521	0.152948	0.806298	8.716186	0.387235	0.27692	5.349185722
1	0.136532	0.174533	0.204648	0.828537	5.934751	0.005449	0.033299	0.093499623
1	-19.1839	0.745745	0.002131	-0.02307	0.860967	-0.14631	-0.14362	0.256344168
0	27.16412	0.910797	0.246449	0.856867	2.159002	0.728153	0.026043	0.588905508
0	-6.99093	1.004685	0.075654	0.224812	10.82222	-0.04807	-0.05886	5.473359877
0	-21.7102	1.411351	0.041324	0.294991	1.199693	-0.97798	-1.00159	0.022376441
0	-90.5317	0.653921	0.012585	-0.15858	0.408513	-0.14781	-0.1451	0.065559167
0	13.37711	1.028521	0.097782	0.597714	29.65166	0.015919	0.016725	1.465092252
0	9.956434	1.028521	0.380813	0.154445	1.338382	0.075655	0.03228	0.488601319
1	30.08472	0.889559	0.199654	0.836887	4.779087	0.30397	0.009622	0.825678696
0	-27.2119	1.366803	0.006619	-0.18511	0.540224	-0.2915	-0.28615	0.141402479
1	-68.9756	1.028521	0.019763	0.009622	2.334578	-0.02214	-0.02447	2.106940738
0	-5.24308	1.729915	0.007854	-0.50485	0.216593	-0.44128	-0.43319	0.103463565
0	-0.14252	1.668555	0.053928	0.895817	1.541789	-0.03124	0.108855	0.583265769
0	-3.978	1.028521	0.024739	0.134236	1.145708	-0.60384	-0.45279	0.56072613
0	20.76059	0.950809	0.07255	0.89451	2.017942	0.507045	0.055747	1.205921484
1	-428.131	0.147353	0.03608	0.20926	2.463353	-164.356	-160.989	0.184245014
0	0.695386	0.108861	0.038313	0.803558	8.683435	0.023467	0.041922	0.151345955
0	2.381909	1.028521	0.256134	0.126703	2.387386	0.017744	-0.00373	2.364350492
0	-30.9451	0.3752	0.173448	0.695563	2.9159	-0.44458	-0.99341	0.023856475
0	7.306135	0.970637	0.024819	0.119016	3.126915	0.08387	0.016978	2.74838493
1	-6.43259	1.239322	0.003198	-0.32327	0.286575	-0.47619	-0.46746	0.123917475
0	26.93389	0.871747	0.091481	0.82013	75.42892	0.193177	-0.09377	4.37711726
0	-166.264	0.066866	0.050903	0.260669	5.049151	-78.4485	-76.5752	0.490668321
1	-0.7858	1.028521	0.005825	0.540809	2.274159	-0.18113	0.027189	0.853240269
1	146.6435	1.028521	0.11624	0.560221	2.509181	0.020951	0.015753	0.57752592
1	50.94889	1.028521	0.09323	0.537065	2.44099	0.025104	0.01818	0.698880274
0	588.7541	1.028521	0.261044	-0.1441	0.663776	0.305032	0.250313	0.161175039
0	2.657541	1.028521	0.305033	0.115653	1.261607	0.043166	0.037349	0.562570104
1	-1.5742	1.028521	0.06127	0.331525	6.832095	-0.03127	-0.03069	0.123499746
0	110.3223	1.028521	0.199175	-0.21672	0.565913	0.229079	0.179978	0.221213951
1	-2.44122	1.028521	0.002886	0.259057	5.25435	-0.02463	-0.02418	0.05260497
0	-27.2104	1.028521	0.082535	-0.35372	0.36349	0.28796	0.215913	0.222905491
0	634.2965	0.95374	0.442492	0.172952	1.748875	1.082383	0.788789	0.04958012

1	-1.7133	0.953737	0.025698	-0.13114	0.936707	-0.19554	-0.19518	0.07197389
0	0.540395	0.953737	0.099198	0.507243	3.613025	0.022591	0.014086	2.116657991
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	8.926564	0.953734	0.008269	0.200257	1.70892	0.144069	0.075891	1.66318365
1	-2.47084	0.953737	0.255931	0.234342	2.012659	-0.02674	-0.02669	0.865667931
0	211.7389	0.953737	0.006109	0.723288	6.955564	0.061033	0.045581	3.906501798
1	136.7963	0.953737	0.165872	0.138018	1.502881	0.178535	0.146105	0.686667681
1	13.7995	0.953736	0.035589	0.646857	9.998395	0.019699	0.021105	0.618143169
0	6.426435	1.194914	0.470256	-0.33033	0.70363	0.460564	2.527061	0.070482507
0	-1.58753	0.953737	0.025698	-0.13114	0.936707	-0.19554	-0.19518	0.07197389
1	1.590123	0.953737	0.00043	-0.14188	0.578668	0.024985	0.009056	0.010929364
0	6.504371	0.953737	0.123888	0.673319	10.29374	0.048389	0.034414	2.893242622
0	2.068131	0.953737	0.202217	0.033651	1.116685	0.062953	0.049391	0.133726496
0	-0.18471	0.953737	0.077213	0.120731	1.229775	-0.0278	0.124395	0.302644842
1	-5.75085	0.953737	0.043271	-1.04385	0.474826	-0.56132	-0.65892	0.111338426
0	9.24804	0.953737	0.025024	0.733357	4.510183	0.106997	0.064785	4.343083753
1	13.67215	0.95373	0.005522	-0.00447	1.058127	0.120895	0.090258	1.029419371
0	3.448298	0.953737	0.022108	0.031128	1.110016	0.03064	0.020495	0.269206883
0	83.76554	1.047895	0.295035	0.348778	1.852337	0.119881	0.083973	0.927590874
0	0.467192	0.953737	0.052361	0.566612	5.45108	0.030842	0.017712	2.254371206
0	-58.6804	0.953681	7.7E-05	-0.04161	0.003368	-0.05573	-0.05659	0.001411823
1	285.6728	0.982816	0.455981	0.178225	1.748875	1.113214	0.812836	0.04958012
0	9.079846	0.953737	0.000126	0.016186	1.190141	0.238755	0.007372	0.922373883
1	-0.35005	0.953737	0.034937	0.070171	1.164485	-0.00237	-0.00284	0.090147954
0	1.902323	0.953737	0.022108	0.031128	1.110016	0.03064	0.020495	0.269206883
0	5.536343	0.953317	0.000428	0.054263	1.166145	0.263044	0.162981	0.021870292
0	15.31857	0.953737	0.293024	0.2287	1.928326	0.111332	0.088722	0.746675475
0	5.649276	0.953737	0.148488	0.481209	7.897896	0.034961	0.03673	4.111221237
1	-55.0273	0.953738	0.002437	0.000443	1.135508	-0.01949	-0.02228	0.781868045
0	1.919515	0.953737	0.021252	0.671795	9.318598	0.002764	0.004215	0.164892266
0	2.107989	0.953737	0.10247	0.70131	10.72914	0.017482	0.006094	3.530448517
1	2.52255	0.95374	0.06452	0.943737	56.7184	0.017184	0.0077	52.36092989
0	3.783924	0.953737	0.655157	0.577569	10.63251	0.092719	0.025329	20.78865336
0	11.72893	0.953737	8.9E-05	0.14436	1.759526	0.442285	-0.05558	1.50828141
0	98.58785	0.953737	0.492883	0.351559	1.910833	0.117363	0.087215	0.550103075
0	12.72081	0.953737	0.044194	0.812697	6.908338	0.163698	0.105269	6.519011277
0	-4.4094	0.953737	0.000281	-0.10821	0.002725	-0.02825	-0.03467	0.004512798
0	-2.02076	0.953734	0.070174	-0.00993	1.060315	-0.33099	-0.16481	0.293200608
1	-43.7897	0.953753	0.026002	-0.04024	0.789424	-0.40424	-0.41281	0.528992107
0	2.56132	0.953737	0.831535	0.781564	25.95409	0.074325	0.013971	4.162561837
0	2.720192	0.953737	0.12572	0.245902	1.665656	0.004843	-0.00059	1.014356141
0	-8.10739	0.953737	0.155981	-2.51419	0.117109	-0.91958	-0.8032	0.009592389
0	27.26176	0.953737	0.060576	0.656369	21.47308	0.028276	0.029271	0.202277143

0	-1.21114	0.953737	0.004699	-0.22297	0.856671	-0.10914	-0.20002	0.061451837
0	431.4595	0.953737	0.314184	0.479769	15.05295	0.237967	0.035211	5.021519351
0	19.17834	0.953737	0.00548	0.028356	7.12117	0.009109	0.026402	5.904303171
0	-7.36276	0.953737	0.155981	-2.51419	0.117109	-0.83512	-0.8032	0.009592389
0	52.36968	0.953737	0.06062	0.538114	2.648129	0.009564	0.008061	0.521754767
0	9.432227	0.953736	0.195153	-0.47657	0.397229	0.173167	0.073841	0.098553837
1	-95.7126	0.953752	0.00903	-0.03245	0.731884	-0.73976	-0.74618	0.501532039
0	148.4916	0.953737	0.120512	0.562628	2.715114	0.014993	0.011915	0.56358763
0	-1.22952	0.953737	0.000952	-0.2562	0.353751	-0.08351	-0.152	0.076640262
1	-20.8489	0.953737	0.000207	-0.0009	0.957717	-0.00874	-0.01404	0.920889714
1	-1.55639	0.953737	0.000353	-0.20522	0.405952	-0.03793	-0.13391	0.079654806
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
0	171.6278	0.953737	0.328786	0.497561	20.17106	0.136577	0.049447	5.831022251
0	-17.1728	0.953737	0.106463	0.691061	7.054984	-1.07309	-1.07107	0.082167011
0	-0.3292	0.953736	0.051528	0.321934	2.445668	-0.00431	-0.01058	0.019751342
1	61.07785	0.953739	0.290448	0.061655	1.227539	0.049301	0.041825	0.403467627
0	-0.31658	0.953737	0.040714	0.312205	2.012043	-0.00334	-0.00333	0.005960253
1	-20.3941	0.953737	0.036164	0.432242	2.254024	-0.04206	-0.05781	0.119475077
1	1.592411	0.953756	0.213496	0.099059	1.697635	0.035978	0.026933	1.874781008
0	-5.0522	0.95376	0.08958	-0.12653	0.729839	-0.22042	-0.22	0.580325872
0	139.4182	0.953737	0.015677	0.771977	7.282748	0.16452	0.123754	3.180108987
1	268.0552	0.953737	0.080597	0.750103	7.01814	0.338262	0.249321	3.254297099
0	14.10946	0.823566	0.020954	0.830625	3.417093	0.475292	0.021112	1.448906736
0	-3.89681	0.37748	0.001444	-0.36963	0.031208	-0.05764	-0.07249	0.026901371
1	-0.99966	0.953737	0.01315	0.004212	1.117762	-0.06422	-0.07411	0.770239773
0	381.7934	0.034703	0.308487	0.92282	29.32635	0.558663	0.538682	19.29923243
1	-12.4189	0.889531	0.220293	0.583482	10.72759	-0.03462	-0.03456	4.604588106
0	0.37921	2.236438	0.00288	0.806571	1.454839	0.049397	0.123191	0.023738359
1	-5.55156	0.953737	0.002291	-0.12472	0.562769	-0.05029	-0.05936	0.082630549
1	2.336479	0.064649	0.012505	0.006657	1.248779	0.027848	0.004734	0.751869402
0	11.42303	0.059637	0.573216	0.660955	12.84767	0.619312	0.479383	0.105894253
0	-4.56021	0.953737	0.002483	-0.03803	0.654815	-0.05234	-0.06384	0.600516146
0	60.42918	0.04259	0.01335	0.232603	6.874586	18.99713	18.60429	0.273281596
0	18.49604	0.802621	0.075366	0.809501	4.167635	0.416185	0.01903	1.341100301
0	-5.80399	0.953737	0.002747	-0.09052	0.646937	-0.07659	-0.08979	0.10086014
0	26.68721	0.88414	0.096872	0.641487	10.8652	0.077433	0.062626	0.737093944
1	4.798981	0.019678	0.011296	0.387344	21.98678	0.44668	0.447597	21.13541442
0	6.323357	0.496982	0.317317	0.270366	1.833191	0.198341	0.1501	0.747681018
1	125.7692	0.953737	0.565943	0.230066	1.58487	0.188774	0.151964	0.300692896
0	-39.6244	0.720244	0.082562	0.017898	1.153085	-0.30355	-0.30297	0.562412794
0	16.52316	0.567095	0.293797	0.326197	2.077062	0.376915	0.299469	1.03133136
1	-15.3856	0.953737	0.225886	0.771101	46.76455	-0.02849	-0.02844	15.49443075
0	3.439603	0.085547	0.062309	0.318352	5.025702	3.989959	1.121605	0.242489718

1	-0.33424	0.675782	0.027773	0.955433	2.573862	-0.05245	0.064609	0.91509511
0	0.558153	1.736113	0.117906	0.848521	1.590947	0.057879	0.103678	0.03233443
0	5.839742	0.062913	0.006572	0.010094	1.405031	0.058279	0.049056	1.178082532
1	378.2074	0.953737	0.583923	0.836869	32.77554	0.572959	0.428964	5.67443099
0	40.85867	0.953737	0.041263	0.614607	84.43156	0.035256	0.036062	4.119876764
1	546.4798	0.025352	0.019284	0.570392	24.97713	0.95737	0.958357	23.21084001
0	26.08131	0.862834	0.221875	0.87023	2.957216	0.593321	0.057221	0.779699725
0	211.5846	0.953737	0.130288	0.80154	9.515582	0.388316	0.282347	5.77624455
0	0.147186	0.161843	0.174329	0.823648	6.479051	0.005464	0.033952	0.10096428
1	-20.6808	0.691522	0.001815	-0.02294	0.93993	-0.14671	-0.14644	0.276809721
0	29.2837	0.844572	0.209936	0.851811	2.357013	0.730186	0.026553	0.635921505
1	-7.53643	0.931633	0.064446	0.223485	11.81477	-0.0482	-0.06001	5.910332302
0	-23.4042	1.30873	0.035202	0.29325	1.309722	-0.98071	-1.02122	0.024162891
0	-97.5957	0.606374	0.010721	-0.15765	0.445979	-0.14822	-0.14794	0.070793164
1	14.42091	0.953737	0.083295	0.594187	32.37113	0.015964	0.017053	1.582059696
0	10.73332	0.953737	0.324394	0.153534	1.46113	0.075866	0.032913	0.527609407
0	32.43219	0.824879	0.170075	0.831949	5.217396	0.304819	0.00981	0.891597772
0	-29.3352	1.267422	0.005639	-0.18402	0.58977	-0.29231	-0.29176	0.15269152
1	-74.3577	0.953737	0.016835	0.009565	2.548691	-0.0222	-0.02495	2.275150946
0	-5.65219	1.604131	0.00669	-0.50187	0.236458	-0.44251	-0.44167	0.111723706
PROBABILITY	X1	X2	X3	X4	X5	X6	X7	X8
1	-0.15364	1.547233	0.045938	0.890531	1.683192	-0.03133	0.110988	0.629831509
0	-4.2884	0.953737	0.021074	0.133444	1.250785	-0.60552	-0.46166	0.605492391
0	22.38051	0.881675	0.061802	0.889232	2.203016	0.508462	0.056839	1.302197711
1	-461.538	0.136639	0.030734	0.208025	2.689277	-164.815	-164.144	0.198954441
0	0.749646	0.100945	0.032637	0.798817	9.479828	0.023533	0.042744	0.163428846
1	2.567766	0.953737	0.218187	0.125956	2.606343	0.017794	-0.0038	2.553111325
0	-33.3597	0.347918	0.147751	0.691459	3.183329	-0.44582	-1.01287	0.025761086
1	7.876223	0.900061	0.021142	0.118313	3.413697	0.084105	0.017311	2.967805625
0	-6.93452	1.14921	0.002724	-0.32136	0.312858	-0.47752	-0.47662	0.133810579
0	29.0355	0.808362	0.077928	0.81529	82.34681	0.193717	-0.09561	4.726569806
0	-179.238	0.062004	0.043361	0.25913	5.512229	-78.6676	-78.0758	0.529841431
1	-0.84712	0.953737	0.004962	0.537618	2.482731	-0.18164	0.027722	0.921359756
0	158.0859	0.953737	0.099019	0.556915	2.739308	0.021009	0.016062	0.623633413
1	54.92436	0.953737	0.079418	0.533895	2.664863	0.025174	0.018536	0.754676242
0	634.6937	0.953737	0.222369	-0.14325	0.724653	0.305884	0.255218	0.174042646
0	2.864905	0.953737	0.259841	0.114971	1.377314	0.043286	0.038081	0.607483581
1	-1.69703	0.953736	0.052193	0.329569	7.458694	-0.03136	-0.03129	0.1333595
0	118.9306	0.953737	0.169666	-0.21544	0.617816	0.229719	0.183505	0.238874839
1	-2.63171	0.953736	0.002458	0.257529	5.736248	-0.0247	-0.02465	0.056804752
0	-29.3336	0.953737	0.070307	-0.35163	0.396827	0.288764	0.220144	0.240701426

PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	1.070979	0.092951	627.0433	32984.7	2.884037	5.669761	102155.256
1	0.163618	0.353754	-1.6937	120238	1.84327	0.086518	238001.652
0	0.362829	0.072646	0.534217	793337	1.569152	1.626299	1336817.034
0	3.038757	0.114374	8.82449	34158.77	2.413762	0.086103	88541.4921
1	2.438135	0.09064	-2.42451	7383.48	2.482704	3.362916	19684.9926
0	0.211983	0.044742	209.3831	290913.8	1.25471	0.162606	391973.6358
0	0.61981	0.116488	135.2411	34511.89	2.800863	1.695911	103802.958
0	0.020888	0.026374	13.64446	148843	1.455851	1.607107	232699.2098
0	9.281506	0.260764	6.353629	27868.55	4.246046	1.714321	101423.826
1	0.163618	0.353754	-1.56892	120238	1.84327	0.086518	238001.652
0	0.144501	0.104753	1.579013	18878.17	16.89087	0.004893	342421.506
0	0.180542	0.026574	6.429993	539764.3	1.40191	5.552447	812593.7398
0	0.402213	0.271889	2.045208	95478.59	1.820421	0.885808	186649.596
1	0.785877	0.277877	-0.18252	56763.84	1.546984	0.330939	94298.904
1	0.04324	0.636601	-5.68508	17304.1	5.525233	0.080956	102671.226
0	1.164617	0.077626	9.142573	68893.31	1.150293	0.383939	85101.03
0	2.643235	0.120404	13.51671	16709.15	4.460423	0.054626	80035.45291
0	0.309303	0.295215	3.443945	164057.7	1.69169	0.089192	298034.478
0	0.346602	0.147994	82.81592	54787	1.68497	2.16099	90225.576
0	0.421009	0.047091	0.461853	628206.3	1.545083	1.324289	1042325.172
0	0.15288	0.014177	-57.984	-3589.76	-71.185	0.006472	274427.966
1	-0.05491	0.092951	282.4061	32984.7	2.884037	5.669761	99133.146
0	0.290152	0.049713	8.977762	71911.81	9.064835	0.003008	700018.0016
1	0.356966	0.275079	-0.34164	75636.18	1.691096	0.151265	137355.75
0	0.309303	0.295215	1.880613	164057.7	1.69169	0.089192	298034.478
0	0.472021	0.209073	5.473124	61029.95	2.220353	0.002439	145581.1623
0	2.398735	0.097166	15.14975	8019.67	2.441278	3.591731	21024.36
0	0.237834	0.025658	5.584774	264129.3	1.914071	6.892645	542904.5723
1	0.004013	0.002526	-54.3896	2013.101	191.0957	1.149059	413109.0637
0	0.004172	0.029649	1.89759	176758.4	1.393436	0.85369	264494.16
0	0.187441	0.026431	2.083897	613065.4	1.350261	4.617386	888942.6
0	0.516228	0.006173	2.493716	45943.38	1.062933	12.44874	52441.62577
0	6.000833	0.021987	3.857244	8810.6	1.638426	35.48819	15501.78
1	0.516147	0.076383	11.59507	86883.42	3.482682	0.001388	324937.494
0	0.314712	0.152477	97.46588	71154.09	1.573357	3.849927	120219.876
0	0.960692	0.050679	12.57821	58415.97	1.11571	1.038598	69989.346
1	0.124939	0.036846	-4.35875	-9964.47	-27.3419	0.009097	292570.866
1	0.501052	0.319197	-1.99763	45011.13	1.677189	0.261837	81068.526
1	-0.39934	0.051901	-43.2673	1298.325	16.97229	0.596675	23662.76976
0	1.018789	0.011432	2.53247	49037.37	1.264016	86.6271	66562.398
0	0.203703	0.150671	2.692089	40727.09	1.893442	0.993771	82810.35
1	0.081012	0.958689	-8.01446	-54151.9	-1.52667	0.19378	88778.592

0	0.028971	0.01171	26.95098	129794.1	1.496098	6.161059	208527.858
1	0.115718	0.377529	-1.19729	79931.78	2.011072	0.014823	172622.016
0	1.626479	0.01249	426.5265	569551	2.016013	29.96019	1233033.966
0	0.024655	0.001706	19.13207	11699.34	32.09809	3.825282	403264.008
1	0.081012	0.958689	-7.2773	-54151.9	-1.52667	0.19378	88778.592
0	0.119385	0.124237	51.77083	6725672	1.30612	0.581138	9433395.594
0	0.521285	0.257201	9.32437	15588.2	52.24394	0.903682	874543.1419
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
1	-0.7308	0.034759	-94.612	781.36	29.36922	0.309413	24642.54576
0	0.107174	0.124602	146.8318	6848183	1.265098	1.151901	9303546.924
1	-0.02517	0.129896	-1.21546	-23052.3	-178.287	0.008733	4413492.846
1	0.010365	0.002871	-20.6039	1801.365	219.0032	0.08607	423644.256
0	0.001569	0.112207	-1.53859	47563.49	90.92684	0.003746	4644242.568
0	1.898664	0.009482	169.6653	422047.9	1.969147	41.29831	892460.268
1	0.599559	0.042038	-16.9762	244812.2	1.315552	3.016269	345851.856
0	0.156411	0.085278	-0.32532	656494.2	2.088388	0.719643	1472282.633
0	0.932372	0.143941	60.39408	82422.44	2.994218	2.40323	265019.0811
0	0.109283	0.120835	-0.31272	884917.4	1.863003	0.401297	1770375.852
1	0.536959	0.133056	-20.1594	263568.9	1.474616	0.323711	417370.968
0	0.528092	0.057594	1.581093	3931.425	4.834091	4.414815	20408.21244
1	0.528234	0.134735	-4.92547	1908.09	7.619666	0.791837	15612.52644
0	0.721859	0.045238	137.8387	122825.2	1.182211	0.412723	155930.67
0	1.068028	0.045912	264.9909	102272.7	1.211214	2.090759	133023.87
0	0.469535	0.149271	13.94821	80648.63	0.812764	0.193616	81515.60573
0	0.793787	0.326705	-3.85149	-7485.3	-3.34306	0.013299	67894.98816
1	-0.06344	0.033237	-0.94508	1753.721	14.87002	0.471202	28004.07319
0	1.321462	0.326705	377.8582	27020.91	0.039081	30.90691	31165.48329
1	0.538528	0.023581	-12.2552	26907.96	1.513659	11.92923	46894.88601
0	1.406837	0.326705	0.375304	63063.4	1.042876	0.004478	30118.31186
0	0.018469	0.089207	-5.38087	215.1103	21.46788	0.03059	4959.061493
0	0.039434	0.201791	2.321147	896.3116	2.084226	1.088867	29594.85803
0	3.660517	0.326705	11.29255	2910.953	0.090692	33.41872	4533.848689
1	-0.0517	0.033211	-4.50475	698.1728	39.04723	0.089057	29275.36566
0	19.08153	0.326705	59.99489	32.19637	0.17397	1.089797	134.6941274
0	0.411144	0.113084	18.28459	72575.34	0.860832	0.9432	79721.32856
1	0.001855	0.077577	-5.73544	281.0552	17.19118	0.042172	5188.557352
0	0.615275	0.025717	26.49208	30391.9	1.369752	4.83947	48223.23002
0	0.443009	0.326705	4.74434	48316.21	0.05235	1.995868	131646.2922
0	3.731526	0.247975	6.271912	2164.533	1.018764	2.924734	4544.380487
0	1.083055	0.163157	124.3311	136363.6	1.864787	4.131229	273071.82
0	0.193533	0.105913	-39.1237	3946.854	4.456069	1.229399	25009.26208
0	3.866551	0.198597	16.33449	3238.95	1.090368	2.963201	6378.218721
1	0.576768	0.006142	-15.2088	52548.6	1.297379	43.79969	73211.16043

0	5.102116	0.326705	3.400976	41.70264	0.243053	2.532412	121.3487555
0	0.742843	0.326705	-0.33039	73811.04	0.513418	0.14289	57433.25574
0	0.784412	0.326705	0.552063	50663.72	0.926646	0.236126	27695.58448
0	0.067556	0.16705	5.777675	736.8293	2.137699	0.710346	25641.85355
0	1.099995	0.009608	373.9548	66840.77	1.187493	72.38617	85235.70758
0	0.035692	0.002684	40.4023	96086.67	1.638928	18.31312	169111.1367
0	0.948534	0.326705	540.2427	37791.48	0.045988	2.644651	70210.15837
0	0.080878	0.185677	25.78308	97617.46	0.769534	1.573127	89167.29613
0	1.005239	0.03455	209.3275	72797.13	1.170023	4.491268	91465.56043
0	0.166288	0.326705	0.14615	92525.69	0.185233	3.745088	108458.7219
1	0.015004	0.087421	-20.4434	699.6725	7.416714	0.034112	7685.60596
0	0.040347	0.272379	28.94933	101232.3	0.683016	1.036619	83847.61708
0	0.413133	0.007751	-7.4455	5985.336	4.16754	10.13724	27422.11697
1	0.243606	0.326705	-23.1344	21796.63	1.203874	0.093518	20535.14843
1	-0.11539	0.144245	-96.1613	88.30242	33.60839	0.139225	5012.534016
0	0.016878	0.00691	14.27479	95066.65	1.67203	14.3575	170695.2708
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	1.102719	0.143474	10.61165	65706.23	2.361044	2.692849	166594.1305
0	0.301127	0.08445	32.06153	69686.69	0.903096	2.773269	78139.58419
1	-0.03108	0.104596	-28.9903	386.1695	16.06286	0.048316	5012.534016
0	0.001987	0.002357	-73.4916	5595.021	71.98629	8.50678	432514.4859
1	-0.05031	0.130038	-5.58749	-432.652	-21.3357	0.036432	5893.62514
1	0.946913	0.326705	-0.1518	59721.18	0.861568	0.10323	34059.61436
0	0.606429	0.271118	-4.23936	55845.88	1.547743	0.092577	92819.48193
0	0.056257	0.309454	22.12513	129377.4	0.651685	0.257299	97941.26857
1	-162.461	0.326705	-456.258	31.39835	0.487872	0.782051	114.819465
0	0.151951	0.326705	0.74126	83010.41	0.124219	1.124104	104619.4186
0	0.27921	0.029872	2.541713	4243.696	5.533655	8.699203	25217.69786
1	-0.13129	0.326705	-32.9773	44553.86	0.402205	1.476515	52751.27309
0	0.383671	0.019483	7.7863	2876.241	6.233963	1.369496	20403.05251
1	-0.06986	0.12793	-6.85521	-140.573	-50.8288	0.021046	6367.827766
0	0.19137	0.004308	28.70735	58304.9	1.046958	25.42048	77340.3487
1	-77.2756	0.326705	-177.182	34.82987	0.220058	2.431465	126.6038212
1	0.585596	0.138671	-0.83742	77541.25	1.261764	0.042618	105065.4917
0	0.126452	0.121548	156.3133	4533.423	1.283649	0.970252	6249.163171
0	0.175784	0.121968	54.36525	3083.386	1.320715	0.775501	4373.067446
0	0.739414	0.150261	627.436	397410.4	6.932174	1.762556	2958406.416
0	2.049645	0.136897	2.832241	7670.49	2.680306	2.260608	22077.846
0	0.121295	0.018781	-1.67759	399101.5	2.776962	3.309849	1190152.328
0	0.707106	0.172784	117.5707	206860.3	8.624568	1.169515	1915858.98
1	0.108387	0.020095	-2.60161	335886.2	3.428425	0.145694	1236619.282
0	0.830942	0.189658	-28.9983	16551	71.90096	0.441508	1277932.95
1	1.105659	0.265358	588.3856	15805.96	6.260441	1.903256	96207.91032

0	0.168916	1.009909	-1.58929	-33057.4	-6.97387	0.029043	224145.5064
0	0.374578	0.207393	0.501281	620221.6	2.087798	0.545925	1258989.291
1	3.137157	0.326517	8.280453	15832.03	5.417171	0.028904	83386.72199
0	2.517086	0.258762	-2.28641	4162.203	4.581158	1.128882	18538.95802
1	0.218848	0.12773	196.4333	260487.4	1.457584	0.054585	369153.4423
0	0.63988	0.332554	126.8977	12593.44	7.98415	0.569293	97759.68526
0	0.021565	0.075295	12.80153	138461.4	1.627905	0.539482	219151.7655
1	9.582057	0.744436	5.961495	-32572.9	-3.77881	0.575473	95519.06322
0	0.168916	1.009909	-1.47248	-33057.4	-6.97387	0.029043	224145.5064
1	0.14918	0.299053	1.477215	-46614.4	-7.11548	0.001642	322486.1728
0	0.186389	0.075865	6.03358	503327.9	1.563817	1.863875	765285.5928
0	0.415238	0.776198	1.918663	3209.925	56.32426	0.297353	175783.1001
0	0.811325	0.793293	-0.17132	9163.558	9.967949	0.111091	88808.94488
1	0.04464	1.817388	-5.33459	-102131	-0.97377	0.027176	96693.84122
0	1.202329	0.22161	8.578748	57201.9	1.441079	0.128883	80146.5591
1	2.728827	0.343735	12.68283	-819.836	-94.5618	0.018337	75375.89329
0	0.319318	0.842788	3.209553	4078.921	70.77575	0.029941	280683.2997
0	0.357825	0.422498	77.70507	28266.22	3.397148	0.725413	84972.76072
1	0.434642	0.134436	0.433378	541996.4	1.862816	0.444544	981642.3608
0	0.15783	0.040473	-54.4252	-10724.8	-24.7842	0.002173	258451.128
0	-0.05669	0.265358	264.9956	15805.96	6.260441	1.903256	93361.74362
0	0.299548	0.141922	8.423179	8676.13	78.15314	0.00101	659263.8671
1	0.368525	0.785305	-0.32335	6964.614	19.1035	0.050778	129359.0775
0	0.319318	0.842788	1.764644	4078.921	70.77575	0.029941	280683.2997
1	0.487305	0.596868	5.135646	5735.868	24.57414	0.000819	137105.617
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	2.47641	0.277391	14.21176	4329.066	4.704266	1.205692	19800.3492
0	0.245535	0.073249	5.240407	240149.2	2.189806	2.31376	511297.3766
1	0.004143	0.007212	-51.0417	115.7762	3456.285	0.385722	389058.3932
0	0.004307	0.084643	1.780587	163417.2	1.567767	0.286571	249095.6552
1	0.19351	0.075456	1.955415	573566	1.501252	1.549989	837189.522
0	0.532944	0.017622	2.339969	45611.41	1.113699	4.178859	49388.54276
1	6.19515	0.06277	3.546089	8237.124	1.822927	11.91287	14599.2866
0	0.532861	0.218061	10.88006	41984.25	7.496814	0.000466	306020.0572
0	0.324903	0.435296	91.45365	38033.14	3.061804	1.292364	113220.8317
0	0.991801	0.144681	11.80096	52259.77	1.297262	0.348642	65914.65762
1	0.128985	0.105188	-4.09018	-29735.5	-9.53059	0.003054	275537.772
0	0.517277	0.911253	-1.87449	-2058.08	-38.1551	0.087895	76348.82222
1	-0.41227	0.14817	-40.6135	-940.396	-24.3739	0.200295	22285.15419
0	1.051779	0.032638	2.376065	47923.24	1.345383	29.07945	62687.22206
0	0.2103	0.430141	2.524231	18139.17	4.42212	0.333594	77989.2395
1	0.083635	2.736895	-7.52051	-210111	-0.40928	0.065049	83610.01824
0	0.029909	0.03343	25.28883	126063	1.602285	2.068177	196387.6383

1	0.119465	1.077781	-1.12348	-38799.8	-4.30953	0.004976	162572.1875
0	1.679147	0.035656	400.2303	544610.4	2.193069	10.0572	1161248.338
1	0.025454	0.00487	17.8437	10507.35	37.17574	1.284091	379786.5038
1	0.083635	2.736895	-6.82945	-210111	-0.40928	0.065049	83610.01824
1	0.123251	0.354676	48.57912	4620401	1.97766	0.195079	8884195.614
0	0.538165	0.734266	8.749515	-395687	-2.14088	0.303353	823628.3816
0	-0.75446	0.09923	-88.7829	-780.707	-30.5751	0.103865	23207.88891
1	0.110644	0.355719	137.7555	4766892	1.890499	0.386676	8761906.564
				-			
0	-0.02598	0.370831	-1.14053	1071638	-3.98931	0.002931	4156545.053
1	0.010701	0.008196	-19.3378	-412.827	-994.023	0.028892	398980.2403
0	0.00162	0.320332	-1.44374	-905197	-4.96976	0.001257	4373860.827
1	1.960146	0.027069	159.2053	408960.8	2.113832	13.86324	840502.396
0	0.618974	0.120011	-15.9298	219608.8	1.52547	1.012517	325716.8123
0	0.161475	0.243455	-0.30534	430594.5	3.311967	0.241574	1386568.259
0	0.962564	0.410928	56.66152	13124.4	19.55969	0.806729	249590.0161
1	0.112822	0.344964	-0.29359	498697.4	3.438679	0.13471	1667306.88
0	0.554347	0.379854	-18.9175	163499	2.472694	0.108665	393072.175
0	0.545192	0.164422	1.479282	1804.037	10.95802	1.481989	19220.07295
0	0.545339	0.384645	-4.6652	-1928.22	-7.84314	0.265808	14703.58553
1	0.745234	0.129147	129.3316	110619.9	1.365405	0.138545	146852.5899
0	1.102613	0.131071	248.6534	91682.17	1.405426	0.701837	125279.3939
0	0.48474	0.426144	13.08824	61889.31	1.101688	0.064994	76769.87355
0	0.819491	0.932686	-3.61452	-23583.4	-1.10372	0.004464	63942.23056
0	-0.0655	0.094887	-0.91396	61.41166	441.7063	0.158176	26373.71259
0	1.364253	0.932686	354.2921	26496.31	0.041456	10.375	29351.06953
0	0.555966	0.067321	-11.5133	25174.01	1.682941	4.004469	44164.72695
0	1.452393	0.932686	0.351895	21222.95	3.223418	0.001503	28364.86305
1	0.019067	0.254671	-5.11659	-592.712	-8.10437	0.010268	4670.351405
0	0.040711	0.57608	2.170883	161.053	12.06556	0.365517	27871.88402
0	3.779051	0.932686	10.59627	2758.042	0.099567	11.21818	4269.893935
0	-0.05338	0.094811	-4.22911	-1075.96	-26.3553	0.029895	27570.99208
1	19.69942	0.932686	56.13465	28.78478	0.202409	0.365829	126.8524111
1	0.424457	0.322837	17.1573	59111.18	1.099387	0.316618	75080.05685
0	0.001915	0.22147	-5.38322	-453.479	-11.0829	0.014157	4886.486314
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	0.635199	0.073418	24.7896	28461.38	1.521445	1.624539	45415.73651
1	0.457355	0.932686	4.4517	46966.81	0.056018	0.669984	123982.0169
0	3.852359	0.707927	5.872118	1102.878	2.079805	0.98179	4279.812586
0	1.118126	0.465786	116.6659	55654.74	4.752674	1.386793	257173.935
1	0.1998	0.302363	-36.7417	310.9553	58.83252	0.412691	23553.25548
0	3.991756	0.566961	15.32728	1879.85	1.954189	0.994703	6006.887151
0	0.595445	0.017535	-14.2717	52023.63	1.363138	14.70291	68948.90222

1	5.267331	0.932686	3.19086	35.43529	0.297536	0.850094	114.2839894
0	0.766897	0.932686	-0.31004	49914.14	0.789736	0.047966	54089.56655
0	0.809812	0.932686	0.517844	20828.28	2.344606	0.079264	26083.18369
0	0.069744	0.476901	5.418514	224.2483	7.306286	0.238453	24149.0183
0	1.135615	0.027428	350.8548	65721.46	1.256255	24.29898	80273.39593
1	0.036848	0.007661	37.90464	95800.58	1.709887	6.147446	159265.707
0	0.979249	0.932686	506.9289	36890.28	0.049005	0.887771	66122.61458
0	0.083497	0.530077	24.19353	70777.29	1.104012	0.528076	83976.09252
0	1.037791	0.098634	196.3202	67429.83	1.31392	1.507653	86140.55488
1	0.171673	0.932686	0.136732	82052.84	0.21727	1.257171	102144.3967
1	0.01549	0.249573	-19.1836	-187.298	-28.8194	0.011451	7238.160012
0	0.041653	0.777596	27.16427	64818.7	1.109588	0.347978	78966.11824
0	0.426511	0.022128	-6.98947	5639.497	4.600874	3.402924	25825.63711
0	0.251495	0.932686	-21.7095	5083.718	5.369099	0.031393	19339.61889
0	-0.11912	0.411795	-90.4332	-751.899	-4.10557	0.046736	4720.710828
0	0.017424	0.019726	13.38292	93447.75	1.769359	4.819602	160757.615
0	1.138427	0.409594	9.956763	22365.76	7.215051	0.90395	156895.2376
1	0.310878	0.24109	30.08479	59643.45	1.097573	0.930946	73590.39958
0	-0.03209	0.298603	-27.209	-885.835	-7.28384	0.016219	4720.710828
1	0.002051	0.006729	-68.963	3762.298	111.3553	2.855601	407334.057
0	-0.05194	0.371237	-5.24302	-2792.51	-3.43844	0.01223	5550.505976
0	0.977576	0.932686	-0.14245	27045.55	1.978949	0.034653	32076.70807
0	0.626066	0.773995	-3.978	10139.67	8.867039	0.031077	87415.65283
0	0.058078	0.883438	20.76102	78869.32	1.11199	0.086372	92239.25574
1	-167.722	0.932686	-428.13	21.74754	0.732682	0.262523	108.1348256
0	0.156871	0.932686	0.695535	76864.24	0.139543	0.377345	98528.6126
0	0.288252	0.085279	2.384558	2890.067	8.452025	2.920195	23749.5564
0	-0.13554	0.932686	-30.9444	33308.4	0.559618	0.495645	49680.16281
0	0.396095	0.055621	7.30625	2206.446	8.452954	0.45972	19215.21342
1	-0.07212	0.365219	-6.43259	-1936.54	-3.83794	0.007065	5997.101144
0	0.197567	0.012298	26.93699	58118.49	1.092528	8.533282	72837.69454
0	-79.7779	0.932686	-166.26	30.10928	0.264789	0.816207	119.233112
1	0.604558	0.395883	-0.7858	51335.01	1.982484	0.014306	98948.71588
1	0.130547	0.346998	146.6716	3169.961	1.909551	0.325699	5885.345047
1	0.181477	0.348199	51.00407	2125.388	1.993018	0.260324	4118.473166
0	0.763357	0.428969	588.7541	-413310	-6.93339	0.591664	2786171.856
0	2.116016	0.390819	2.657618	2186.474	9.780829	0.758853	20792.50262
1	0.125223	0.053616	-1.57417	360482.6	3.198021	1.111068	1120863.213
0	0.730003	0.493268	110.3224	-397362	-4.67026	0.392589	1804320.171
1	0.111897	0.057367	-2.44122	292342.3	4.097392	0.048907	1164624.921
0	0.85785	0.541441	-27.2105	-426607	-2.90164	0.148208	1203533.362
0	1.061462	0.280569	634.2965	19638.84	4.759386	1.653619	98002.3836
1	0.162164	1.067799	-1.7133	-14717.5	-14.7962	0.025234	228326.2762

0	0.359605	0.219281	0.540396	700844.2	1.745239	0.474319	1282472.003
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	3.011753	0.345234	8.926565	19827.19	4.085913	0.025112	84942.05402
1	2.416469	0.273595	-2.46571	4990.111	3.609353	0.980814	18884.74731
0	0.210099	0.135052	211.7575	288459	1.243303	0.047425	376038.9051
1	0.614302	0.351617	136.7989	16793.8	5.655424	0.494622	99583.1023
1	0.020703	0.079611	13.80028	152523	1.39593	0.468722	223239.3918
0	9.199025	0.787109	6.426628	-27122	-4.28677	0.499992	97300.6881
0	0.162164	1.067799	-1.5874	-14717.5	-14.7962	0.025234	228326.2762
1	0.143217	0.316195	1.592128	-41739.4	-7.50619	0.001427	328501.1961
0	0.178938	0.080213	6.504371	554262.5	1.341413	1.619403	779559.7262
0	0.398639	0.820692	2.068337	16354.13	10.44248	0.258351	179061.8126
0	0.778893	0.838766	-0.18469	16628.53	5.188682	0.09652	90465.4124
1	0.042856	1.921566	-5.75085	-94800.6	-0.99093	0.023611	98497.3781
0	1.154268	0.234313	9.248121	64042.16	1.215831	0.111978	81641.4555
1	2.619745	0.363438	13.67241	1547.011	47.33588	0.015932	76781.80707
0	0.306554	0.891099	3.458243	26733.38	10.20039	0.026014	285918.6143
0	0.343521	0.446717	83.76788	34535.61	2.626371	0.630265	86557.6756
0	0.417268	0.142142	0.467193	603387	1.580562	0.386237	999951.9882
0	0.151521	0.042793	-58.6732	-10708.2	-23.4472	0.001888	263271.7674
1	-0.05443	0.280569	285.6728	19638.84	4.759386	1.653619	95103.1301
0	0.287574	0.150057	9.080341	18274.49	35.04841	0.000877	671560.4796
1	0.353794	0.83032	-0.3488	17164.17	7.321976	0.044117	131771.8875
0	0.306554	0.891099	1.902335	26733.38	10.20039	0.026014	285918.6143
0	0.467826	0.631082	5.536368	13960.18	9.537348	0.000711	139662.9158
0	2.377419	0.293292	15.32037	5237.548	3.672815	1.047549	20169.666
0	0.23572	0.077447	5.649304	265370	1.871872	2.01028	520834.113
1	0.003977	0.007626	-55.0249	390.5958	967.7033	0.33513	396315.1238
0	0.004135	0.089495	1.919522	180164.8	1.34323	0.248984	253741.796
0	0.185775	0.079781	2.107993	631326.9	1.28832	1.346687	852804.81
1	0.51164	0.018632	2.522553	49813.42	0.963243	3.630746	50309.73957
0	5.947506	0.066369	3.816978	9067.508	1.564221	10.35034	14871.593
0	0.51156	0.230561	11.72901	52063.38	5.71047	0.000405	311727.9539
0	0.311916	0.460248	98.58938	46111.73	2.385444	1.122853	115332.6306
0	0.952155	0.152974	12.72162	57878.77	1.106412	0.302913	67144.1001
0	0.123829	0.111218	-4.40934	-29690.9	-9.01596	0.002653	280677.1121
0	0.4966	0.963488	-2.02076	4310.495	17.20792	0.076366	77772.8831
1	-0.39579	0.156663	-43.7835	-714.255	-30.3127	0.174024	22700.81766
0	1.009735	0.034509	2.561444	52444.84	1.161263	25.2653	63856.4663
0	0.201893	0.454797	2.721043	22938.06	3.30318	0.289839	79443.8975
0	0.080292	2.893781	-8.10733	-207532	-0.39141	0.056517	85169.5152
0	0.028714	0.035346	27.26203	138068.7	1.38189	1.796909	200050.6673
0	0.11469	1.139563	-1.21114	-25797.3	-6.12247	0.004323	165604.4896

0	1.612025	0.0377	431.4597	597705.2	1.887523	8.738062	1182907.982
0	0.024436	0.00515	19.2274	11630.73	31.72393	1.115666	386870.2948
0	0.080292	2.893781	-7.3624	-207532	-0.39141	0.056517	85169.5152
0	0.118324	0.375007	52.36968	5334613	1.617966	0.169492	9049903.939
0	0.516652	0.776356	9.432227	-374454	-2.13691	0.263564	838990.7267
1	-0.72431	0.104918	-95.7109	-634.265	-35.5489	0.090242	23640.76326
0	0.106222	0.37611	148.5025	5491111	1.550218	0.335959	8925333.949
0	-0.02495	0.392088	-1.22952	1023224	-3.94654	0.002547	4234073.075
1	0.010273	0.008666	-20.8471	-142.035	-2729.05	0.025103	406422.0336
1	0.001556	0.338694	-1.55639	-854965	-4.97017	0.001092	4455442.231
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
0	1.881791	0.028621	171.6278	448045.1	1.822517	12.04489	856179.4758
0	0.594231	0.12689	-17.1727	243128.4	1.301544	0.879712	331792.0936
0	0.155021	0.257411	-0.32917	501291.8	2.68723	0.209888	1412430.579
1	0.924086	0.434484	61.082	23972.45	10.11509	0.700916	254245.3777
0	0.108312	0.364739	-0.31651	597930.1	2.709065	0.117041	1698405.546
1	0.532187	0.401628	-20.3937	192334.2	1.985501	0.094412	400403.7708
1	0.523399	0.173848	1.594365	2264.723	8.245239	1.287606	19578.56641
0	0.52354	0.406694	-5.03265	-1569.56	-9.10142	0.230944	14977.83731
0	0.715444	0.13655	139.4224	122398.8	1.165625	0.120373	149591.6895
1	1.058537	0.138585	268.0554	101510.7	1.199008	0.609782	127616.1095
0	0.465363	0.450572	14.10949	70141.12	0.918211	0.056469	78201.78789
0	0.786733	0.98615	-3.89659	-23489.9	-1.04671	0.003879	65134.88326
1	-0.06288	0.100326	-0.98743	302.7223	84.64107	0.137429	26865.636
0	1.309719	0.98615	381.9155	28983.53	0.035799	9.014178	29898.5267
1	0.533742	0.07118	-12.4128	27709.2	1.444237	3.47923	44988.48897
0	1.394335	0.98615	0.379332	28984.42	2.229455	0.001306	28893.92546
1	0.018305	0.269269	-5.52117	-534.197	-8.49381	0.008922	4757.462962
1	0.039084	0.609102	2.339707	278.1383	6.59928	0.317575	28391.75136
0	3.627988	0.98615	11.42307	3030.633	0.08559	9.746764	4349.536145
0	-0.05124	0.100246	-4.55927	-926.884	-28.8989	0.025974	28085.24718
0	18.91196	0.98615	60.50196	31.88263	0.172615	0.317846	129.2184666
0	0.40749	0.341343	18.49606	66372.32	0.924856	0.27509	76480.45268
0	0.001839	0.234165	-5.80337	-392.487	-12.0956	0.0123	4977.629226
0	0.609807	0.077627	26.71841	31323.47	1.30582	1.411459	46262.8324
1	0.439073	0.98615	4.799048	51434.04	0.048318	0.582107	126294.5338
0	3.698365	0.748507	6.329271	1351.238	1.603465	0.853015	4359.639799
1	1.07343	0.492487	125.7692	71967.22	3.471735	1.204897	261970.7521
0	0.191813	0.319695	-39.6109	845.7175	20.43295	0.358561	23992.57162
0	3.83219	0.59946	16.52324	2240.432	1.548813	0.864235	6118.927819
1	0.571643	0.01854	-15.3853	56836.76	1.178562	12.77443	70234.93953
0	5.056775	0.98615	3.439803	39.53685	0.251893	0.738593	116.4156183

1	0.736241	0.98615	-0.33423	57790.45	0.644303	0.041675	55098.44702
0	0.777441	0.98615	0.558236	26881.67	1.715964	0.068867	26569.68814
0	0.066956	0.504238	5.841078	316.0756	4.89639	0.207177	24599.44663
1	1.09022	0.029	378.2279	71865.42	1.08519	21.11184	81770.65809
0	0.035375	0.0081	40.86175	104569.1	1.479699	5.341127	162236.3365
1	0.940105	0.98615	546.4832	40376.97	0.042292	0.771328	67355.93588
0	0.080159	0.560463	26.08131	80964.46	0.911621	0.458811	85542.41751
0	0.996306	0.104288	211.6307	74321.14	1.126029	1.309904	87747.2515
0	0.164811	0.98615	0.147369	90987.62	0.185077	1.092277	104049.5975
1	0.014871	0.263879	-20.6805	-80.8209	-63.0864	0.009949	7373.166423
0	0.039988	0.822169	29.28384	75796.41	0.896303	0.302336	80438.99702
1	0.409462	0.023397	-7.53508	6201.497	3.952076	2.956586	26307.33779
0	0.241441	0.98615	-23.4036	7874.786	3.274049	0.027275	19700.34213
0	-0.11436	0.4354	-97.5054	-703.378	-4.14558	0.040606	4808.76169
1	0.016728	0.020857	14.42624	102187.5	1.528368	4.187448	163756.0716
0	1.09292	0.433073	10.73362	30440.29	5.007435	0.785385	159821.653
0	0.298451	0.25491	32.43225	66476.6	0.930183	0.80884	74963.01027
0	-0.0308	0.315719	-29.3325	-789.374	-7.72097	0.014092	4808.76169
1	0.001969	0.007115	-74.3577	4360.364	90.75744	2.481052	414931.6659
0	-0.04986	0.392517	-5.65219	-2718.25	-3.33663	0.010626	5654.034206
PROBABILITY	X9	X10	X11	X12	X13	X14	X15
1	0.938498	0.98615	-0.15364	34061	1.484274	0.030108	32675.00394
0	0.601039	0.818362	-4.2884	17429.76	4.872502	0.027001	89046.13262
0	0.055757	0.934079	22.38051	93090.39	0.889908	0.075043	93959.70553
1	-161.018	0.98615	-461.538	25.07324	0.600283	0.22809	110.1517601
0	0.1506	0.98615	0.749646	84723.62	0.119583	0.327851	100366.3717
1	0.276729	0.090167	2.567766	3341.93	6.904184	2.537173	24192.53395
0	-0.13013	0.98615	-33.3597	37909.55	0.464449	0.430634	50606.79893
1	0.380262	0.05881	7.876223	2500.775	7.044795	0.399422	19573.61625
0	-0.06924	0.386154	-6.93452	-1862.83	-3.76871	0.006138	6108.959282
0	0.18967	0.013003	29.0355	63439.78	0.945423	7.414029	74196.26575
0	-76.5889	0.98615	-179.238	33.51013	0.224732	0.709151	121.4570521
1	0.580392	0.418576	-0.84712	59662.44	1.611252	0.01243	100794.3108
0	0.125328	0.366889	158.0859	3648.696	1.567071	0.282979	5995.118707
1	0.174222	0.368159	54.92436	2452.474	1.631497	0.226179	4195.291071
0	0.732843	0.453558	634.6937	-338045	-8.00732	0.51406	2838139.63
0	2.031431	0.413222	2.864905	3149.537	6.413784	0.659319	21180.3251
1	0.120217	0.056689	-1.69703	398706.2	2.731201	0.965337	1141769.592
0	0.700822	0.521543	118.9306	-349407	-5.01691	0.341096	1837974.413
1	0.107424	0.060655	-2.63171	325043.4	3.480959	0.042493	1186347.546
0	0.823558	0.572478	-29.3336	-403750	-2.89601	0.128768	1225981.708