ST. MARY'S UNIVERSITY

SCHOOL OF GRADUATE STUDIES,

INSTITUTE OF AGRICULTURE AND DEVELOPMENT STUDIES

DEFAULT PROBABILITY MODELING FOR AGRICULTURAL LOANS OF THE DEVELOPMENT BANK OF ETHIOPIA

BY

ALEMAYEHU LEMMA

JUNE, 2014

ADDIS ABABA, ETHIOPIA

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ENDORSEMENT

This thesis has been submitted to St. Mary's University, School of Graduate Studies for examination with my approval as a university advisor.

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Advisor Signature

St. Mary's University, Addis Ababa June, 2014

DECLARATION

I, the undersigned, declare that this thesis is my original work, prepared under the guidance of Dr. Milkesa Wakjira. All sources of materials used for the thesis have been duly acknowledged. I further confirm that the thesis has not been submitted either in part or in full to any other higher learning institution for the purpose of earning any degree.

________________________ ________________________

Name Signature

St. Mary's University, Addis Ababa June, 2014

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ABSTRACT

Credit risk is the most prominent risk facing banks. Its effective management is vital for banks success. Banks are expected to improve their credit risk management system due to increasing financial loss resulting from loan default. Regulators also emphasized the importance of quantification and credit risk modeling. Currently, credit risk management has become an important topic for financial institutions, since the business of financial service is highly associated with uncertainty. However, credit risk model for agricultural loan is still in its infancy stage. The general objective of this study was to model agricultural loan default probability after examining significant factors determining default. The objective was accomplished by conceptualizing a theory of loan default for agricultural borrowers and deriving a model predictive of loan default. About 322 firm-year observations spanning the time period 2007 to 2013, consisting of balance sheet and gain and loss account of a particular firm for a particular year were used in the study. A binary logit model was used to analyze the relationships between historical data available at loan origination time and loan performance. The result indicated a strong and direct relationship between key financial variables and probability of default. Leverage, liquidity, profitability and debt coverage ratio at loan origination were found to be good indicators of the probability of default. However, loan size, loan duration and farm type were not statistically significant in explaining agricultural loan default probability. The derived default probability model is applicable to agricultural loans which could be used as a benchmark for agricultural lending banks when setting internal rating models. Banks can provide special service required to help avoid default among those borrowers considered more likely to default by developing a more sophisticated default model.

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LIST OF ACRONYMS

BCA	Basel Capital Accord
CBE	Commercial Bank of Ethiopia
DBE	Development Bank of Ethiopia
EAD	Exposure at Default
EL	Expected Loss
IRBA	Internal Rating Based Approach
LGD	Loss Given Default
LPM	Linear Probability Model
NL	Nonperforming Loan
NBE	National Bank of Ethiopia
OLS	Ordinary Least Square
PD	Probability of Default
SPSS	Statistical Package for Social Science

I. INTRODUCTION

1.1. Background

Banks perform the essential function of channeling funds from those with surplus funds to those with shortages of funds. The banking business requires balance between risk and return characteristics of credit transactions which exposes banks to various risks adversely affecting their profitability and hence sustainability. In banking business, risk is inevitable event where the success or failure of banks is directly related to their risk management capacity. Thus, quantifying risks and developing an effective risk management strategy are important objectives of banks.

To prevent the resulting economic and financial crisis of bank failures, regulators also give emphasis to the development of efficient credit risk management system. All over the world, the management of credit risks has always been a major component of bank management.

Credit risk, operational risk, market risk, liquidity risk, legal risk and reputation risk are the major risks banks are facing (Kim, 2005). Though banks face different risks, credit risk is regarded as the primary cause of bank failures in recent years and it is the most visible risk faced by bank management (Gup, 2004). Barry (2002) defined credit risk as the loss resulting from failure of obligors to honor their payments. Recognizing the sever effects of credit risk, recently the banking industry has undergone a significant development in the understanding of credit risk and its management system. Different statistical methods have been proposed concerning the estimation of key risk parameters like default probabilities, a cornerstone of credit risk modeling. The other two components are loss-given-default or loss severity and exposure at default (Hayden, 2002).

Credit risk is an essential aspect of portfolio management for banks. The Basel Committee on Bank Supervision defined credit risk as the potential that a bank borrower or counterparty will fail to meet its obligation in accordance with agreed terms. Banks typically evaluate credit risk based on a borrower's default probability and subsequent losses. In risk evaluation process, an investigation and clear understanding of the relationship between loan default and borrower characteristics is given due attention.

By developing an accurate credit risk rating system, banks are able to identify loans that have lower probability of default versus loans that have a higher probability of default. Thus, they better rate loans, price loans and may benefit from capital savings.

Almost all financial institutions, small or large, national or international, public or private, utilize some type of risk rating system. This system serves a variety of purposes: facilitating loan origination; monitoring loan portfolio safety and soundness; determining capital requirements; and servicing loans (Koenig, et al, 2008). Moreover, by developing an accurate credit risk rating system, banks will be able to identify loans that have lower probability of default versus loans that have a higher probability of default.

Risk management is also emphasized by supervisory organ, New Basel Accord (Basel Committee on Banking Supervision, 2004). The Basel Committee on Banking Supervision is a committee of banking supervision authorities that was established by a group of banking regulators. The Committee encourages banks to construct an internal rating approach to measuring credit risk endogenously.

The most important step in credit risk management is to determine probability of default (PD). Probability of default has much significance as it is one of the core parts for better allocation of capital, better pricing, client judgment, regulatory compliance and finally better monitoring of high risky customers. Due to these important reasons, financial institutions need to assure that the probability of default determination is sophisticated and more importantly shows the true picture of the portfolio in present as well as future scenarios.

Credit risk modeling for agricultural loans should base on the attributes of agricultural sector and its borrowers. The agriculture sector typically experiences different cash flow patterns and return to production assets. Agricultural loan credit risk modeling is closely related to net cash flows like other retail loan categories, exhibiting annual cycles (Kim, 2005. Thus, banks lending to the agricultural sector requires a different credit risk model for their loan portfolio that captures the characteristics unique to agriculture.

1.2. Statement of the Problem

Generally speaking, credit risk modeling of agricultural loan portfolios is still at its early stage. There are only few literature citations that can be found on agricultural default modeling. Most portfolio credit risk models being used have been developed for corporate exposures and are not generally applicable to agricultural loan portfolio partly due to data restrictions (Kim, 2004). Agricultural loan default modeling should account for attributes of the agricultural sector and its borrowers.

The agricultural sector typically experiences cash flow problems resulting from low return to production assets. The performance of the sector is also influenced by economic cycles and is highly correlated with farm typology, commodity, and geographical location (ibid). Credit risk for agricultural loans is closely related to a farm's net cash flows like other retail loan categories, showing annual cycles. Agricultural banks need a unique credit risk model for their loan portfolio that captures these and other characteristics unique to agriculture. Thus, using appropriate theory and methodology, there is a need to enhance and contribute to agricultural loan default modeling.

The present study is therefore intended to fill this gap by estimating the probability of default by applying statistical models on historical loan origination data of agricultural loans from the Development Bank of Ethiopia.

1.3. Objectives of the Study

1.3.1. General Objective

The general objective of this study is to develop a default probability model for agricultural loan portfolios from the Development Bank of Ethiopia.

1.3.2. Specific Objectives

The specific objectives of the study are:

1. Examine financial ratios important for evaluating the probability of agricultural loan default.
2. Examine whether loan size and loan duration explains agricultural loan default.
3. Examine whether specialization in production of certain agricultural commodity is related to agricultural loan default.

1.4. Significance of the Study

The study has important contribution in agricultural credit risk management of banks. The study adds to the stock of the existing scanty literature where it can be used as a reference for further studies. The results of the study also provide a guideline for credit risk management of agricultural lending institutions. The model application and approaches introduced in the study can serve as a basis for agricultural lending institutions to develop a more objective model and comply with regulatory requirements. The study is expected to help banks focus on the important decision variables while making loan decisions. More specifically, the outcome enables agricultural lenders identify loans that require special attention and hence significantly improve their asset quality and reduce default loss.

1.5. Scope and Limitation of the Study

Even though losses given default and exposure at default are also important components of risk measuring, the scope of the study is limited to studying probability of default as credit risk measurement and management is found in the default probability. The study used data available at loan origination time as there are no yearly financial statements in database. Specifically, the study was conducted using agricultural loan data supplied by the Corporate Credit Process of the Development Bank of Ethiopia, as data on loans from Branches are not covered by the existing network.

1.6. Definition of Terms and Concepts

Credit: In this study, credit is defined as a contractual agreement in which a borrower receives something of value now and agrees to repay the lender at some date in the future, generally with interest (Investopedia Dictionary).

Credit Risk: Credit Risk is defined as the degree of value fluctuations in debt instruments and derivatives due to changes in the underlying credit quality of borrowers (Lopez, 2000). In this study it is defined as the potential that a bank borrower or counterparty will fail to meet its obligation in accordance with agreed terms.

Default: There have been different arguments about the definition of default. It has been defined as liquidation, bankruptcy filing, loan loss or charge off, non-performing loan, or loan delayed in payment obligation are used at many banks as proxies of loan default. In this study, default is considered to have occurred with regard to a particular obligor when either the bank considers that the obligor is unlikely to pay its credit obligations to the bank in full, without recourse by the bank to actions such as realizing security or the obligor is past due more than 90 days on any material credit obligation to the bank (The Basel Committee, 2004).

Expected Loss (EL): EL as defined by Barry is adopted for this study. Barry (2002) defined EL as the loss that can be expected from holding an asset and it is calculated as the product of three components; 1. The Probability of Default (PD), 2. The Loss Given Default (LGD) and 3. The Exposure at Default (EAD).

Probability of Default (PD): It is defined as the frequency that a loan will default and is expressed in percentage terms.

Loss Given Default (LGD): It measures the cost for the financial institution when the loan defaults. It is expressed in percentage terms.

Exposure at Default (EAD): It is the amount of money outstanding when the default occurs.

1.7. Organization of the Thesis

The thesis is organized into five chapters. Chapter one covers background of the study, statement of the problem, objectives of the study, research hypothesis, definition of terms, significance, scope and limitation of the study. Chapter two presents review of related literature which summarizes the theoretical and empirical literatures on the subject matter. The research data, data processing techniques, model building process, method of data analysis and description of variables used in the research are discussed in chapter three. Chapter four presents the findings of the research. The last chapter presents the conclusion and recommendation drawn from the research.

II. REVIEW OF RELATED LITERATURE

2.1. Theoretical Review

2.1.1. Introduction to Risk Management

Risk is the basic element that drives financial sector of any economy. Without risk, the financial system would be vastly simplified (Kim, 2005). In the real world however, risk is always there. Financial Institutions, should therefore manage the risk efficiently to survive in this uncertain world. Only efficient banks that have good risk management system will survive in the market in the long run. The effective management of credit risk is a critical component of comprehensive risk management essential for long-term success of a banking institution.

Credit risk is the oldest and biggest risk that bank, by virtue of its very nature of business, inherits. Credit Risk is defined as the degree of value fluctuations in debt instruments and derivatives due to changes in the underlying credit quality of borrowers (Lopez and Saidenberg, 2000). The Basel Committee on Bank Supervision (The Basel Committee, 2000) defines credit risk as "*the potential that a bank borrower or counterparty will fail to meet its obligation in accordance with agreed term*." Credit risk is mostly associated with loans and securities in banks' balance sheet and it is the largest risk confronted by banks (Featherstone, 2006).

The effect of high credit risk on a bank is loss in assets and interest income. This loss reduces the bank's profit, depletes its capital and might at the extreme lead to bank failure. High levels of problem loans cause banks to increase spending on monitoring, working out, and/or selling off these loans and possibly become more diligent in administering the portion of their existing loan portfolio that is currently performing (Berger and Deyoung, 1997). Credit risk is regarded as the primary cause of bank failures in recent years and it is the most visible risk faced by bank management (Gup, 2004). This has led to the development of modern credit risk management techniques.

Credit risk modeling has been developed rapidly over the past decades to become a key component in the risk management system of the banking industry. Credit risk models help bank management measure the credit risk associated with individual loans as well as their asset portfolio (Kim, 2005). They enable a bank to forecast possible credit losses over the coming year, to differentiate loan price over borrowers having different risk, to determine the loan loss reserves and risk-based capital requirements, to evaluate credit concentration and set concentrate limits and to measure risk adjusted profitability (Lopez, 2001).

2.1.2. Risk in Banks

Neoclassical microeconomic theory models assume that banking business is run to maximize expected profit and states the role of bank as a financial intermediary that performs both brokerage and a risk transformation function (O'Hara, 1983). This way, banks are viewed as firms accepting and managing risks to maximize profit. Bessis in 2002, assuming banks as a profit maximizing firms, defines banking risk as the adverse impact on profitability of several distinct sources of uncertainty. Since bank is subject to credit and market risk on the funds it lends and to withdrawal risk on the funds it borrows, it must contend with risk associated with both its assets and its liabilities (Bessis, 2002).

In fact, banks face numerous risks affecting profitability throughout its business line. The management of these risks has always been a major component of bank management. The major sources of banking risks are classified into four categories: credit risk, market risk, operational risk and performance risk (Kim, 2005).

The classification of bank risk by researchers and regulatory agency however differs. The Basel Committee (1988) lists the key risks faced by banks as credit risk, country and transfer risk, market risk, interest rate risk, liquidity risk, operational risk, legal risk and reputation risk. The Committee in 2000 defined Credit risk, the main focus of this study, as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms.

Apart from credit risk, market risk is the change in asset value due to changes in underlying economic factors such as interest rates, exchange rates and equity and commodity prices. Operational risk comes from costs incurred through mistakes made in carrying out transactions such as settlement failures, failures to meet regulatory requirements and untimely collections (Kim, 2005). Performance risk encompasses losses resulting from failure to properly monitor employees or to use appropriate methods.

Credit risk is usually associated with loans and securities, which are the primary source of bank revenue. Loans are the major and most obvious source of credit risk to banks. However, other sources of credit risk exist throughout their activities. The Basel Committee states that banks are increasingly facing credit risk other than loans, including acceptances, inter bank transactions, trade financing, foreign exchange transactions, bonds and equities in the extension of commitments, guarantees and in settlement of transactions.

2.1.3. Credit Risk Components in Banks

There are three components of credit risk in a bank‘s loan portfolio; transaction risk, intrinsic risk and concentration risk. Transaction risk is associated with the instability in credit quality and earnings resulting from how banks underwrite individual loan transactions. Selection, underwriting, and operations of loans are under the scope of transaction risk (O'Hara, 1983).

Intrinsic risk focuses on the risk inherent in certain lines of business and loans to certain industry types. Intrinsic risk addresses the susceptibility to historic, predictive, and lending risk factors that characterize an industry or line of business. Historic elements address prior performance and stability of the industry or line of business. Predictive elements focus on characteristics that are subject to change and could positively or negatively affect future performance. Lending elements focus on how the collateral and terms offered in the industry or line of business affect the intrinsic risk.

Concentration risk is the aggregation of transaction and intrinsic risk within the portfolio and may result from loans to one borrower or one industry, geographic area or lines of business. Bank must define acceptable portfolio concentrations for each of these aggregations. Portfolio concentration management allows a bank to avoid disaster. Concentrations within a portfolio will determine the magnitude of problems a bank will experience under adverse conditions.

2.1.4. Credit Risk Management in Banks

Banks make profit from the difference between the interest rate they charge to borrowers and the interest rate they pay to depositors. Lending has always been the primary functions of banks and accurately assessing a borrower‘s credit worthiness has always been the only method of lending successfully (Kim, 2005). Banks always try to make loans that will be fully repaid with interest on due date. Therefore, banks are directly concerned about borrowers repaying their loans on a timely basis so that the performance of banks can be maximized. Otherwise, if banks are not able to manage credit risks effectively, they will not be profitable and be in business in the long run.

Lack of diversification of credit risk has been the primary reason for many bank failures. Banks have a comparative advantage in making loans to entities with which they have an ongoing relationship. This creates excessive concentrations in geographic or industrial sectors.

2.1.5. Credit Risk Management Guide Line in Ethiopia

As per the credit risk guide line of National Bank of Ethiopia (NBE), in Ethiopia it is the responsibility of the board of directors to approve credit risk strategy and policies. Each bank should develop a strategy that sets the objectives of its credit-granting activities and adopts the necessary policies and procedures for conducting such activities. It is also the management's responsibility to implement the credit risk strategy approved by the board of directors. Management also develops policies and procedures for identifying, measuring, monitoring and controlling credit risk. Such policies and procedures should address credit risk in all of the bank's activities at both the individual credit and portfolio levels.

Banks operating in Ethiopia need to understand to whom they are granting credit (NBE directive No. SBB/46/2010). Prior to entering into any new credit relationship, consideration should be given to the integrity and reputation of the party as well as their legal capacity to assume the liability. Therefore, prior to entering into any new credit relationship, a bank shall become familiar with the borrower or counterparty and be confident that it is dealing with creditworthy individual or organization (NBE Directive No. SBB/46/2010).

The NBE Directive also states that establishing sound and well defined credit granting criteria is essential to approve credit in a safe and sound manner. In order to conduct an effective credit granting program, banks shall receive sufficient information to enable a comprehensive assessment of the risk profile of the counterparty. In order to maintain a sound credit portfolio, a bank must have a clearly established process in place for approving new credits as well as extensions or renewal and refinancing of existing credits (Ibid).

Each credit proposal should be subject to careful analysis by a qualified credit analyst. An effective evaluation process establishes minimum requirements for the information on which the analysis is to be based. The information received will be the basis for any internal evaluation or rating assigned to the credit and its accuracy and adequacy is critical to management making appropriate judgments about the acceptability of the credit.

Exposure limits are also needed in all areas of the bank‘s activities that involve credit risk. Banks should establish credit limits for individual counterparties and groups of connected counterparties. Such limits are frequently based on internal risk ratings that allow higher exposure limits for counterparties with higher ratings. Limits established by banks shouldn't be higher than regulatory limits set by NBE. Limits should also be established for particular industries or economic sectors, geographic regions specific products, a class of security and group of associated borrowers (NBE Directive No. SBB/52/2012).

Excessive concentration makes a bank vulnerable to adverse changes in the area in which the credit is concentrated and to violations of statutory and regulatory limits. Sound and prudent risk management involves the minimization of concentration risk by diversifying the credit portfolio.

Internal risk rating system is a good means of differentiating the degree of credit risk in the different credit exposures of a bank. This allows more accurate determination of the overall characteristics of the credit portfolio, problem credits, and the adequacy of loan loss reserves. Detailed and sophisticated internal risk rating systems can also be used to determine internal capital allocation, pricing of credits, and profitability of transactions and relationships.

In accordance with the NBE directive No. SBB/52/2012, banks need to develop and implement comprehensive procedures and information systems for monitoring the condition of individual counterparties across the banks' various portfolios. These procedures should define the criteria for identifying and reporting potential problem credits and other transactions to ensure that they are subject to more frequent monitoring, corrective action and proper classification and provisioning.

2.1.6. Risk Grading System in Development Bank of Ethiopia

Like any financial institutions, credit risk is a major problem to the Development Bank of Ethiopia. Looking at the portfolio, the size of non-performing loans has continued to rise from one financial year to the subsequent due to loan repayment default by debtors and this has contributed to the deterioration of the portfolio quality. To cope up with the credit risk threats, the bank has developed different mechanisms in evaluating risks.

1. Pre-Credit Risk

Pre credit risk analysis covers the period from the appearance of the borrower till the preparation of the loan contract. Pre-credit risk consists of potential risks that are likely to occur due to failure to examine rigorously the credit worthiness of the borrowers and bankability of the project. Before credits are sanctioned, the bank undertakes a series of screening measures to ascertain the bankability of the project. The loan applications are checked for their completeness and meeting the standard criterion set by the bank.

The yardsticks used to measure the risk associated at the pre-appraisal stage are divided into two broad categories i.e. applicant strength and collateral strength. In compliance with this credit risk rating guideline of the bank, the Credit Process/branch rates the risk grades of projects and recommend those projects with risk grades AAA, AA, A, BBB, or BB for their further appraisals (DBE Credit Risk Manual, 2010).

2. Post-Credit Risk

Post credit risk begins after the first disbursement onwards. The benchmarks used to measure risk at post credit stage are divided into two broad categories i.e. business assessment and collateral strength. The business assessment includes measure of default risk, character of the borrower, project management risk, market risk and capital adequacy risk (DBE Credit Risk Manual, 2010). Collateral strength is concerned with value of assets pledged as collateral for the loan.

3. Loan Review

Loan review is a vital tool in identifying problem loans and in taking mitigating measures in a timely manner. It also helps in maintaining the overall health of the bank's loan portfolio. The loan review function of the bank is given to the Risk Management Process of the bank and accordingly the process undertakes a continuous and independent loan review throughout the bank in order to improve operating efficiencies and asset quality of the bank. In order to maintain the overall health of the bank, the loan review function generally addresses the following main issues (DBE Revised Procedural Manual on Credit Policy, 2012):

- ❖ Lending activities are in compliance with prudent lending standards as approved and adopted by the Board of Management of the bank;
- ❖ Assess the adequacy of and adherence to loan policies and procedures and to monitor compliance with relevant laws and regulations;
- ❖ The Board of Management and Senior Management is adequately informed of the risks and potential loss exposure in outstanding loans or advances with an objective assessment of the overall portfolio quality;
- ❖ Problem or deteriorating loans or advances are properly and timely identified, classified and placed on non-accrual status in accordance with the requirements laid out by NBE;
- ❖ Identify relevant trends affecting the loan portfolio and isolate potential problem areas;
- ❖ Uncollectible non-performing loans or advances are written off as appropriate;
- ❖ Ensure that every obligor is assigned a risk grade accurately and timely and is reviewed semi-annually at a minimum. Assure also that the risk rating process is reviewed at least once every three years and more often if necessary;
- ❖ Ensure that sector, sub-sector, single borrower and related parties loan concentration exposure limits set by the Bank is maintained;

2.1.7. Measuring Credit Risk

Most credit rating models are based on two sources of credit risk; default risk and migration risk (Kim, 2005). Default risk is the risk that counterparty default, which happens when they fail to meet their debt obligation. Default when it happens will result in a total or partial loss of any amount lent to the counterparty. However, migration risk is the risk that obligors' credit rating goes down into a lower loan classification (Ibid).

The deterioration of credit rating doesn't imply default but it does imply that the probability of default increased (Bessis, 2002). The Basel Committee suggests a default to occur when: the bank considers that the obligor is unlikely to pay its credit obligations to the bank in full and/or the obligor is past due more than 90 days on any credit obligation to the bank.

Default risk can be measured at individual loan level and at portfolio level, which is called portfolio credit risk. The most direct measure of default risk is the probability of default (PD), which is the likelihood that a loan will fall into default (Kim, 2005). When measuring default risk at portfolio level, it relates to the measure of expected loss at default. The expected loss is disaggregated into three elements which are analyzed separately (Barry, 2002). These elements are probability of default, loss given default and exposure at default.

As Barry explains, the probability of default indicates a loss may occur, while loss given default indicates how it affects the firm. Whereas, loss given default is net of any recovery attributable to liquidation of secured property and any deficiency judgments rendered through foreclosure and bankruptcy proceedings. Both PD and LGD are expressed in percentage terms which are then applied to the loan level, which is called the exposure at default, to determine expected loss.

2.1.8. Credit Risk and the Basel Committee

The Bank for International Settlements (BIS), headquartered in Basel, Switzerland, serves as a bank for central banks and helped set international monetary policy. In 1975, the central bank governors of the G-10 countries convened to form the Basel Committee on Banking Supervision. Although the committee had no supranational authority, it articulated banking standards and guidelines with the goal of closing gaps in international supervisory coverage. The Committee developed several sets of standards such as the Capital Accord (1988) and the Core Principals (1997). These standards have been gradually introduced and received powerful backing not only in member countries but also in all countries with active international banks (Kim, 2005).

The Basel Committee published its first report on capital adequacy in 1988, called the 1988 Capital Accord (Basel I). The report highlighted dangerously low capital levels at the world's largest banks and proposed the creation of uniform minimum capital standards. By setting minimum capital standards, the 1988 Accord protected bank owners, depositors, creditors and deposit insurers against financial distress. Over 100 countries have since applied the Basel framework to their banking system (The Basel Committee, 2001).

The Basel Committee (1988) announced plans to revise the capital standards and described its objective to provide approaches which are both more comprehensive and more sensitive to risks than the 1988 Accord, while maintaining the overall level of regulatory capital. After extensive interactions with banks and industry groups, the Basel Committee published the final document, "International Convergence of Capital Measurement and Capital Standard, a Revised Framework," which is widely known as "Basel II" in June 2004.

The new regulatory framework consisted of three pillars. The first pillar is minimum capital requirements, maintained the same definition of regulatory capital and the 8% target capital ratio. The second pillar is supervisory review, called for increased regulatory oversight. The third pillar is market discipline which outlined requirements for increased bank disclosure.

The new proposal also focused on individual asset classes and not on a bank's entire asset portfolio or its integrated balance sheet. Rather than using just a few broad asset classes, however, the new proposal set capital requirements based on credit risk within asset classes using one of two approaches. Under the standardized approach, banks would use the ratings on their borrowers or loans supplied by credit rating agencies approved by regulators with risk weights set by the Basel Committee to determine the minimum amount of capital they needed to hold. In contrast, under the internal ratings based (IRB) approach, banks would classify their loans into risk categories using their own internal data.

Although the IRB approaches implied there would be different standards at different banks, the committee favored the internal approaches because they incorporated a bank's specific risk profile, loan loss experience and risk-mitigation techniques. Under the IRB approach, banks must categorize banking book exposures into broad classes of assets with different underlying risk characteristics. The classes of assets are corporate, sovereign, bank, retail and equity.

2.1.9. Credit Risk Models

A credit risk model helps bank management evaluate the credit risk of individual loans as well as its whole portfolio. It also enables a bank to forecast possible credit losses over the coming years, to differentiate loan price over borrowers exhibiting different risk, to determine the loan loss reserves and the risk based capital requirements, to evaluate credit concentration and set concentrate limits (Lopez and Saidenberg, 2000).

There are two broad branches of credit risk models; stand-alone credit risk and portfolio credit risk models. The stand-alone credit risk model attempts to evaluate credit risk at the transaction or account level such as a firm or individual borrower whereas, the portfolio credit risk model measures credit risk at the portfolio level.

Banks are increasingly measuring credit risk at the portfolio level in addition to the transaction level. First, banks realized that traditional classifications of good and bad loans are not sufficient to properly manage their credit risk because all credits could potentially default under a particular extraordinary economic scenario. Second, possible errors in selecting and pricing individual loans are decreasing, but diversification and timing impacts on bank credit risk is increasing. Bank management needs more proactive risk measures for loan exposure after the loan has been originated (Kim, 2005).

2.1.9.1.Transaction Level Credit-Risk Model

Banks have made wide use of the probability of default as a proxy variable for the risk associated in an individual credit. There have been three broad categories of traditional models used to estimate the credit risk at individual loan level: expert systems, internal and external credit rating, and credit scoring models.

Most financial institutions used to rely virtually on subjective analysis or the so called banker expert system to assess the credit risk of borrowers. Bank loan officers used information on various borrower characteristics, which are called as the “5 Cs” of credit. They are character of borrower, capital, capacity, collateral and condition (Tayler, 1991).

The credit decision is left in the hands of the lending officers. The expertise, judgment and weighting of certain factors are the most important determinants in the decision to grant loans. The loan officers can examine as many points as possible, but must include the five C’s. Because experts evaluated the “5 Cs” subjectively, they are inconsistent. Moreover, expert systems specify no weighting scheme that would order the “5 Cs” in terms of their relative importance in forecasting default probability.

This is a summary indicator of risk for banks’ individual credit exposures (Tayler, 1991). They depend on a number of factors, quantitative financial ratios and qualitative variables. The credit rating usually includes from six to ten different ranks, but they are not quantitative measures of risk but rather a qualitative ordering (Bessis, 2002). External credit ratings refer to the rating system or ratings from the system independently made outside the banks or creditors, while internal credit ratings are those constructed in the banks for their own use.

As Kim (2005) explained, banks internal rating systems differ from external ratings in architecture and operating design as well as in the uses to which ratings are applied, because they are designed by bank personnel and are usually not revealed to outsiders.

Credit scoring began as a tool for banks to decide whether or not to grant credit to consumers (Thomas, 2000). New statistical methodologies have been utilized in this area, and remarkable development in computer systems enables banks to apply a variety of new models. These days, many banks are implementing credit scoring models in their credit decision-making. When constructing a credit scoring model, banks are confronted by two critical issues, the functional form and which explanatory variables to use in the model (Kim, 2005).

There is no common consensus on which variables should be included in a credit scoring model because economic theory hardly supports the issue (Ibid). As a practical matter, the choice of the explanatory variables largely relies on data availability. There are four methodological forms of parametric models in the credit scoring literature: discriminant analysis, linear probability models, logit models and probit models.

Linear probability model (LPM), logit models and probit models employ standard statistical techniques and provide banks with the probability of default for a borrower. LPM uses a least square regression approach, where the dependent variable is 1, if a borrower is in default or 0 otherwise. Logit and probit models are different from LPM in that they assume the probability of default is logistic or normal distribution.

2.1.9.2. Portfolio Credit Risk Model

Portfolio credit risk model is a methodology that estimates the probability of default and loan loss for a loan portfolio over a particular time horizon. It usually combines the probabilities of default for individual loans and estimates the probability of default at portfolio level by aggregation (Lopez, 2001). Portfolio credit risk modeling is a process to find specific solutions to the two main problems; the modeling of the probability of default for individual loans and the construction of the joint distribution of default by taking into account the correlations between defaults in the portfolio (Duffie, 1999).

Portfolio credit risk models were initially developed for commercial use in the 1990s. These models include proprietary applications constructed for internal use by financial institutions as well as others intended for sale or distribution to third parties (Kim, 2005). Current portfolio credit risk models can be traced to three alternative forms: option-based structural models, reduced form (actuarial) models, and multi-factor econometric model.

The option-based structural model consists of default model and correlation model. Default models directly model the default process and are typically calibrated to market variables such as the obligor's stock price. The option-based structural model specifies the correlations which assigns default correlations to pairs of obligations.

As stated by Kim, the reduced form model uses a mathematical technique common in loss distribution modeling developed in the insurance industry, the so called actuarial model. It is assumed that at the end of the risk horizon the borrower is in one of two states, default or non-default.

The multi-factor econometric model evaluates systemic credit risk of a country, an industry or a portfolio segment as opposed to an individual exposure. This model assumes a homogenous credit standing for firms within a portfolio segment and the existence of causal relationship between credit risk of a portfolio segment and economic conditions associated with the loan portfolio (Bessis, 2002).

2.2. Review of Empirical Studies

Some empirical studies have been conducted to develop agricultural loan default probability model using financial ratios and qualitative variables. There are scanty studies analyzing attributes of the borrower including financial, managerial, earnings and cash flow, quality of assets and liquidity of firms in relation to agriculture sector.

Jouault and Featherstone, (2006) developed agricultural loan default probability in a French Bank utilizing three independent variable, leverage, profitability and liquidity. The binary logit regression model result shows that all the three variables are statistically significant in explaining default. The coefficient for leverage is positive and the coefficients for profitability and liquidity are negative as expected.

Katchova and Barry (2005) also found other financial ratios solvency and liquidity in personal assets to be strong indicator of default. Liquidity in personal assets was found to be highly significant and every increase in personal equity decreased the probability of default.

They also studied the effect of loan size on default probability and as per their study loan size did not appear to be an important factor influencing loan default. While small farms were indicated to be more likely to default, the parameter was not statistically significant. Larger loan amounts do not necessarily increase default risk, as long as a large loan amount is consistent with a larger farm size.

The length of the loan was examined to determine if longer loans have higher probability of default by adding the variable length to default model. The length of the loan was statistically significant in predicting probability of default of loans; the longer the loan length is, the higher the probability of default (Katchova and Barry 2005).

By including effect of commitment amount on the estimated default model, Roessler, (2003) found origination financial ratio statistically significant in explaining default.

However, the coefficient estimate of commitment amount was not statistically different from zero. Thus, commitment loan size did not have a statistically significant impact in explaining whether a loan will enter default status or not. This is consistent with the findings of Featherstone, Roessler and Barry (2003).

Featherstone and Boessen, (1994) analyzed default according to farm type. The farm types were classified in to four groups; agriculture, agricultural service, wine production and others. For these farm types of agriculture, the independent variables were regressed on the default outcome. For the agricultural model, all the signs obtained were as expected, but only the working capital variable was statistically significant. The overall model was statistically significant in predicting the probability of default of loans as indicated by the likelihood ratio of chi-square. The statistics of the wine production and agricultural services models indicate that neither the independent variables nor the overall model are good indicators of the probability of default. For activities composed of hunting, forestry and fishing oriented businesses, all the coefficients of the independent variables had the expected signs and are statistically significant in predicting the probability of default except the working capital variable. This is a similar finding with Katchova and Barry (2005), where specialization in production of a certain commodities was indicated to be one of the strongest default indicators.

2.3. Conceptual Framework

The fundamental goal of a credit risk rating system is to estimate the risk of a given transaction. The building block for quantifying credit risk is Expected Loss (EL), the loss that can be expected from holding an asset (Barry, 2002). This is calculated as the product of three components: the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD).

The probability of default (PD) is defined as the frequency that a loan will default. It is an indication of the likelihood and frequency that a loan will enter default status. The loss given default (LGD) measures the cost for the financial institution when the loan defaults. PD and LGD are expressed in percentage terms which are then applied to the EAD which is the amount of money outstanding when the default occurs. EAD is what the institution has at risk when the loan does enter default status.

The relationship between the four credit risk parameters; EL, PD, LGD and EAD can be stated as:

$$EL = (PD*LGD) * EAD$$

Though, EL is disaggregated in to three elements, as Barry explains they are separately analyzed. Literatures examine these aspects separately due to the inability to easily track loans through the default and recovery process (Katchova and Barry (2005).

Credit risk measurement and management is found in the probability and financial consequences of obligator default (Kim, 2005). The Basel Accord suggests eight criteria for banks to measure when implementing a risk-rating system including evaluation of a firm's repayment capacity, solvency, earnings, operating leverage, financial efficiency, liquidity, management and industry standing. This study focused only on the PD component of the equation.

III. RESEARCH METHODOLOGY

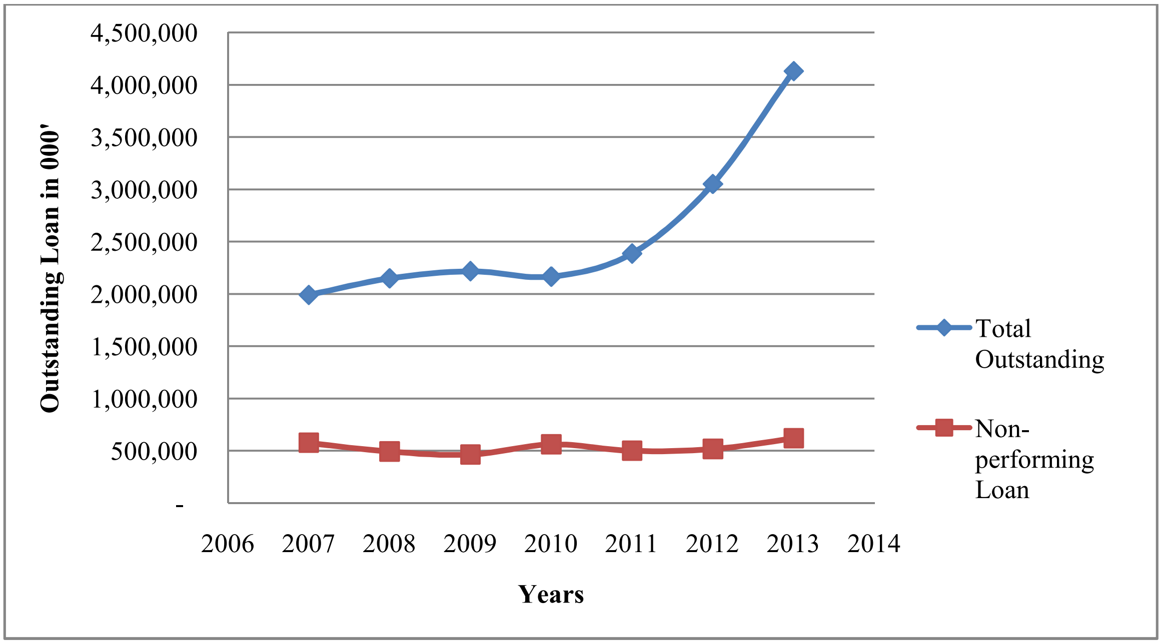
3.1. Research Data

The necessary research data for the statistical analysis were supplied by Development Bank of Ethiopia, a government owned bank financing diverse agricultural activities. The Development Bank of Ethiopia is a specialized financial institution established to promote the national development agenda through development finance and close technical support to viable projects in the priority areas of the government.

About 322 firm-year observations spanning the time period 2007 to 2013 were used in the present study. Each observation consists of the balance sheet and the gain and loss account of a particular firm for a particular year.

The data set was classified on customer level and loan level basis. The customer level data corresponds mainly to the origination financial data. The customer level data are the customer ID, year of the financial data, total equity, long-term debt, working capital, total assets, total equity and liabilities, sales, profit before tax and amortization, bank interest, net income and etc. The loan level data contain customer ID, date of origination, date of maturity, code of loan and description, loan amount, loan duration, amount due, type of collateral, indicators of default, frequency of payment, activity of the business and etc.

Figure 1 below illustrates the trend of total agricultural loan outstanding and defaulted agricultural loan in each year. From 2007 to 2013, the total agricultural loan outstanding has been increasing, but the highest increase is observed since 2011. Non-performing loan has also increased in magnitude. However, the share of the non-performing loan out of the total agricultural loan has slightly decreased.



Source: DBE Annual Performance Report, June 2013

Figure 1: Trend of Total Outstanding Agricultural Loan and Nonperforming Loan

The historical trend for the default rate is depicted in Figure 2 below. From the highest point in 2007, default rate has decreased to around 15% in 2013. The default rate has fallen from the previous year in 2007 through 2009, whereas the default rate increased from the previous year only in year, 2010.

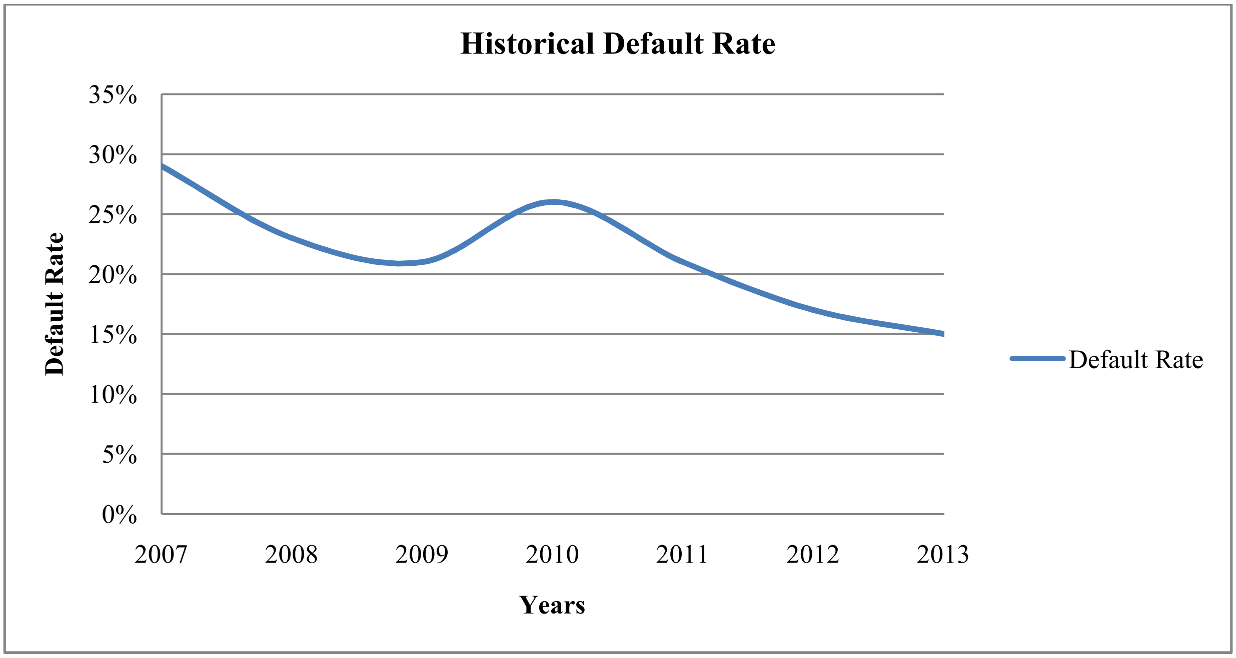


Figure 2: Historical Default Rate

3.2. Data Processing

Before actually using the collected raw data, the data set was checked for mistakes and whether the default information was available. The default information was checked if it was available and reliable for all borrowers. In addition, missing information with respect to the financial input data was properly managed. Due to mistakes in the data, the data set was cleaned as certain loan types were excluded, like public firms and those that do not represent the typical Ethiopian company. In addition, the data set was rechecked for fulfillment of all the required data and hence observations lacking default information were excluded.

Once the qualities of the basic origination financial data were guaranteed, potential explanatory variables were selected. Typically, ratios were formed to standardize the available information. Overall, financial ratios representing the most important credit risk factor, which includes leverage, liquidity, profitability, debt coverage, loan size, loan duration and farm type were selected. The selection was based on the existing theory and previous empirical findings. Moreover, preliminary regression was also run to select the most important potential variables.

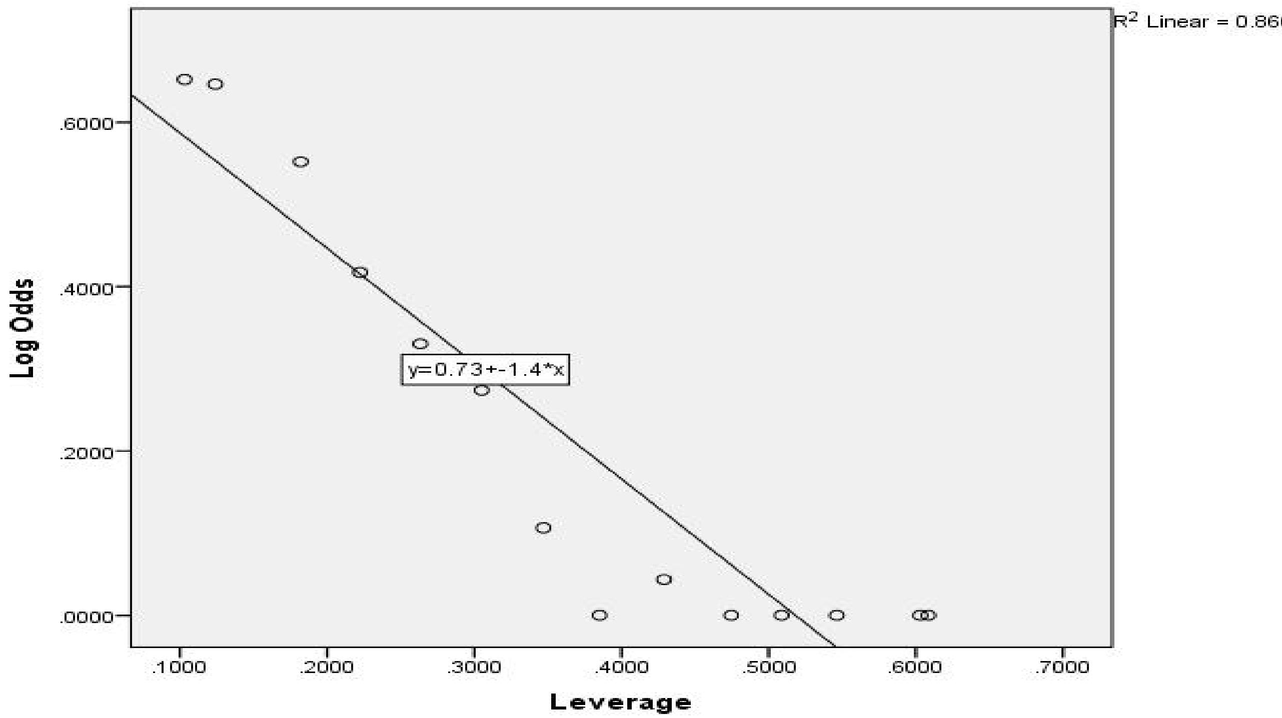
After calculation of the input financial ratios, the data were tested for potential outliers using scatter plots, because outliers can severely distort the estimated parameters. It was checked that the outliers are genuine, but not just an error. The values of input variables are checked whether they are within the range of possible scores for the variable. However, outliers found are fewer, some are excluded and some are replaced by a less extreme value, thus including the data in the analysis but not allowing the value to distort the statistics.

After having selected the candidate input ratios and checking for outliers, the next step was to test whether the underlying assumptions of the selected model, logit model apply to the data. This is because; logit model implies a linear relationship between the log odds and the input variables. Linearity assumption was tested by dividing the explanatory variables into groups that all contain the same number of observations, calculating the historical default rate respectively, the empirical log odd within each group and estimating a linear regression of the log odds on the mean values of the ratio intervals (Hayden, 2002).

Accordingly, the input variables were divided into about 14 equal groups that all contain the same number of observations and within each group the historical default rate and the empirical log odd were calculated. Finally a linear regression of the log odd on the mean values of the variable intervals was estimated.

It was found that for most accounting ratios considered in this study, the linearity assumption is indeed valid. As an example, the relationship between the variable leverage, as defined by total liabilities divided by total assets and the empirical log odd and the estimated linear regression is depicted in Figure 3. The fit of the regression is as high as 86.6%. In same way, the linearity assumption for the rest variables was investigated and found acceptable.

Figure 3: Linearity test for Leverage (Liabilities/Assets) Ratio



After verifying that the underlying assumptions of a logistic regression were valid, the model building process was started. The selected explanatory variables were used to derive the final multivariate logit model. In the final step, the significance of the derived logit model was tested using different statistical tests to verify model robustness and goodness of fit. The goodness of fit of a logit model was tested using Hosmer-Lemeshow test, Likelihood Ratio test and classification techniques.

3.3. Method of Data Analysis

3.3.1. Descriptive Statistics

Descriptive statistics were used to analyze and summarize the characteristics of the data set collected. Descriptive statistics like mean, percentage, standard deviation and range were used to provide a summary statistics of the financial ratios for both defaulted and non defaulted loans. Comparisons and analysis of different categories of the data with respect to the desired characteristics were made using descriptive statistics.

3.3.2. Econometric Model

Statistical rating systems primarily involve a search for explanatory variables which provides sound and reliable forecast of the deterioration of a borrower's situation. Every statistical model uses borrower's characteristics indicators which were collected historically and were available for defaulting and non-defaulting borrowers.

Different statistical methods can be used to predict default performance of borrowers. A common feature of the methods is that they estimate the correlation between the borrowers' characteristics and the state of default in the past and use this information to build a forecasting model (Hayden, 2002). The forecasting model is designed to assess the creditworthiness of borrowers with unknown performance.

As stated by Hayden (2002), the statistical model used in default modeling includes linear discriminant analysis, linear regressions, logit and probit models. Linear regression model establishes a linear relationship between the borrowers' characteristics and the default variable which is estimated with the ordinary least squares method (OLS). Though OLS estimators are well known and easily available, the estimation of coefficients is inefficient and additionally the standard errors of the estimated coefficients are biased.

Discriminant analysis is a classification technique applied to corporate bankruptcies by Altman as early as 1968 (Kim, 2005). Linear discriminant analysis is based on the estimation of a linear discriminant function with the task of separating individual groups, in this case defaulting and non defaulting borrowers, according to specific characteristics. It has been pointed that the weakness of this method is that the method doesn't produce a probability of default. Furthermore, when the models are estimated, the OLS estimator used is not efficient because it basically assumes that explanatory variables of two groups are normally distributed and have the same variance-covariance matrix (Kim, 2005).

Logit and probit models are econometric techniques designed for analyzing binary dependent variables. The logit and probit models generally leads to similar estimation results. Logit and probit models are different from LPM in that they assume the probability of default is logistic or normal distribution. Application of logit and probit models in credit scoring began in the 1980s under the background development of quantitative choice model. Numerous papers have been published and logit and probit analysis became the most preferred models in credit scoring research (Hayden, 2002).

The model selected in this research for agricultural loan default modeling is binary logit model. I decided in favor of the logit model mainly because of two reasons. Firstly, there are findings that show differences in performance between logit and probit models are either non-existing or marginal. Secondly, the logit model allows to easily check whether the empirical dependence between the potential input variables and default risk is economically meaningful (Hayden, 2002).

The latent-variable approach of the logit and probit model assumes an unobservable (latent) variable y* which is related to the borrower's characteristics in the following way:

$$y_i^* = bx_i + u_i$$

The variable y_i^* is metrically scaled and triggers the value of the binary default variable y_i:

$$yi = \begin{cases} 1, & if\ yi > 0 \\ 0, & otherwise \end{cases}$$

This means that the default event sets in when the latent variable exceeds the threshold zero. If the residuals are assumed to follow a logistic distribution, the result is the logit model:

$$f(bxi) = e^{bxi} \Big/ 1 + e^{bxi}$$

What is more important is the fact that the coefficients of the logit model can be more easily interpreted. To see this we transform the logit model in the following way:

$$pi \Big/ 1 - pi = e^{bxi}$$

The left-hand side is the odds, i.e. the relation between the default probability and the probability of survival. The transformed coefficients e^b are called the odds-ratios. The strengths of logit model are that the method is theoretically sound, the results generated can be interpreted directly as default probabilities, the significance of the model and the individual coefficients can be tested and therefore, the stability of the model can be assessed more effectively than in other models (Hayden, 2002).

The binomial logit model utilizes a maximum likelihood estimation which is consistent and asymptotically efficient, and with large samples produces normally distributed coefficient estimates (Kim, 2005). Therefore, the logit model was preferred to develop agricultural default model in this study.

3.3.2.1. Model Variables

1. Dependent Variable

The dependent variable of the models is log odds ratio of default. This binary variable takes the value 1 if the loan defaulted and 0 otherwise. A default is considered to have occurred with regard to a particular obligor when either one or both of the following two events have taken place (The Basel Committee, 2004).

- *"The bank considers that the obligor is unlikely to pay its credit obligations to the Banking group 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 banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstanding."*

2. Independent Variables

Hayden (2002) stated mainly three main possible model input categories: accounting variables, market-based variables such as market equity value and soft facts such as the firm's competitive position or management skills. Historically banks used to rely on the expertise of loan officers and managers who looked at a combination of accounting and qualitative variables to come up with an assessment of credit risk. Researchers have tried to formalize the dependence between accounting variables and credit quality. In this study, leverage, liquidity, profitability, debt coverage, loan size, loan duration and farm types are included as explanatory variables of the default model.

A. Leverage Ratio:

Leverage indicates debt proportion and in this study is defined as liability divided by total asset. This variable measures debt proportion of the assets of the firm. Financial debt is defined as all the debt to financial institution. Highly leveraged firms, which use high debt to finance their asset, are likely to default as the owners' equity contribution is lower. Alternatively, the higher the amount of equity compared to the amount of asset, the lower the risk of default. If the ratio is less than one-half, most of the company's assets are financed through equity. If the ratio is greater than one-half, most of the company's assets are financed through debt. A leverage ratio of one indicates a case where the entire asset of the firm is financed by debt.

Featherstone, and Boessen, (1994), studied probability of default of agricultural loans and found the coefficient of leverage significant. According to their study, the variable leverage has positive relationship with agricultural loan default. Theories also suggest the same relationship.

B. Liquidity Ratio:

Liquidity ratio is defined as working capital divided by total assets and this variable is expected to have negative relationship. It is a common variable used in most credit decisions of lenders. The variable measures the amount of working capital available to the firm in relation to the size of company's asset. Companies that have more working capital may be more successful since they can expand quickly with internal resources.

In 2008, Steven studied default probability for FSA Direct Loans and found that liquidity in personal assets highly significant and has a negative relation with default. That is, the higher cash and other liquid positions or the lower short-term liabilities, the lower the risk of default. However, companies with low working capital may find it difficult to hold the funds necessary for growth.

C. Profitability Ratio:

Profitability ratio is defined as the rate of return on assets, which equals the fiscal years net income divided by the total assets of the company. The coefficient of this variable is expected to be negative since higher profitability should result in a smaller risk of default.

It is expressed as a decimal in this study. Alternatively, as higher profitability raises firm's equity value, a company's creditworthiness is positively related to its profitability.

Carey (1998) studied the profitability variable and found its coefficient significant in explaining default. The relationship of profitability variable with default is found to be negative. Similarly, in 2001 Gallagher found that financial ratios such as leverage, liquidity and profitability significant variables that influence loan performance.

D. Debt Coverage:

Debt coverage ratio is a ratio obtained by dividing income before interest and tax by interest expense. Previous studies found that the variable has a statistically significant impact on default probability. The higher the amount of debt, the higher the amount of bank interest and hence the coefficient of this ratio is expected to be positive as well. Also, the lower the profit, the lower the ratio is the higher the probability of default.

E. Loan Size:

Loan size is another variable examined to know whether it explains agricultural loan default or not. Loan size is the total amount of loan approved and in this study it is expressed in birr. Katchova and Barry (2005), examined if loan size explains agricultural loan default. In their result, loan size did not appear to be a very important factor influencing loan default. Borrowers with larger amounts borrowed were more likely to default; though the level of significance did not reach the 5 percent threshold.

F. Loan Duration:

Loan duration was also hypothesized to explain loan default. The length of the loan is computed by calculating the number of years between the origination date and the maturity date of the loan. The longer loan duration, the lower the amount of principal loan repaid, the higher the risk of default. The idea behind the coefficient would be that the longer the duration, the lower the amount of principal repaid, the higher the risk of default.

G. Farm Type:

Specialization in production of a certain agricultural commodity is one of default indicators. In 2003, Roessler studied the variable farm type and found that Farms specializing in dairy and grain production less likely to default. The default probability was higher among cotton farmers and specialty crops producers, which included vegetables, fruit, nuts, greenhouse and nursery products.

In the present study, the variable farm type was also analyzed according to the major agricultural activities of firms. Farm type was disaggregated into eight separate binary dummy variables based on DBE's commodity classification. These farm types included cereals, coffee, cotton, livestock, floriculture, fruits and vegetables, oil seeds and poultry production.

3.3.2.2. Research Hypotheses

Based on theoretical and previous empirical studies conducted, the following hypotheses were tested to identify significant variables that determine probability of agricultural loan default.

Hypothesis 1: Leverage, defined as total liabilities divided by total assets has a positive relationship with agricultural loan default.

Hypothesis 2: Profitability, defined as the rate of return on assets (net income divided by total assets) has a negative relationship with agricultural loan default.

Hypothesis 3: Liquidity, working capital divided by total assets, has negative relationship with agricultural loan default.

Hypothesis 4: Debt Coverage is obtained by dividing income before interest and tax by interest expense and was hypothesized to have a negative relation with agricultural loan default.

Hypothesis 5: Loan Size is hypothesized to have either positive or negative relationship with agricultural loan default.

Hypothesis 6: Loan duration is hypothesized to have negative relationship with default. The longer the loan duration, the lower the amount of principal loan repaid, the higher the risk of agricultural loan default.

The empirical model to estimate the probability of default takes the following form:

$$\textbf{\textit{Log Odds = PD/ (1-PD)}} = Y_{i=} b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 + b_7x_7 + u_{i;}$$

Where: $b_{0:}$ *is the constant,*

bi: are coefficients,

$x_{1:}$ *is Leverage,*

$x_{2:}$ *is Liquidity,*

$x_{3:}$ *is Profitability,*

$x_{4:}$ *is Debt Coverage,*

$x_{5:}$ *is Loan Size,*

$x_{6:}$ *is Loan Duration*

$x_{7:}$ *is Farm Type and*

$u_{i:}$ *is Error term.*

IV. RESULT AND DISCUSSION

4.1. Descriptive Result

4.1.1. Activity of Firms

Data series utilized in the estimation of the default model cover the period 2007 to 2013. Figure 4 below depicts the distribution of the data considered in the present study according to type of firms' activity. The total number of loans studied in this research is 70, yielding 322 firm yearly observation data.

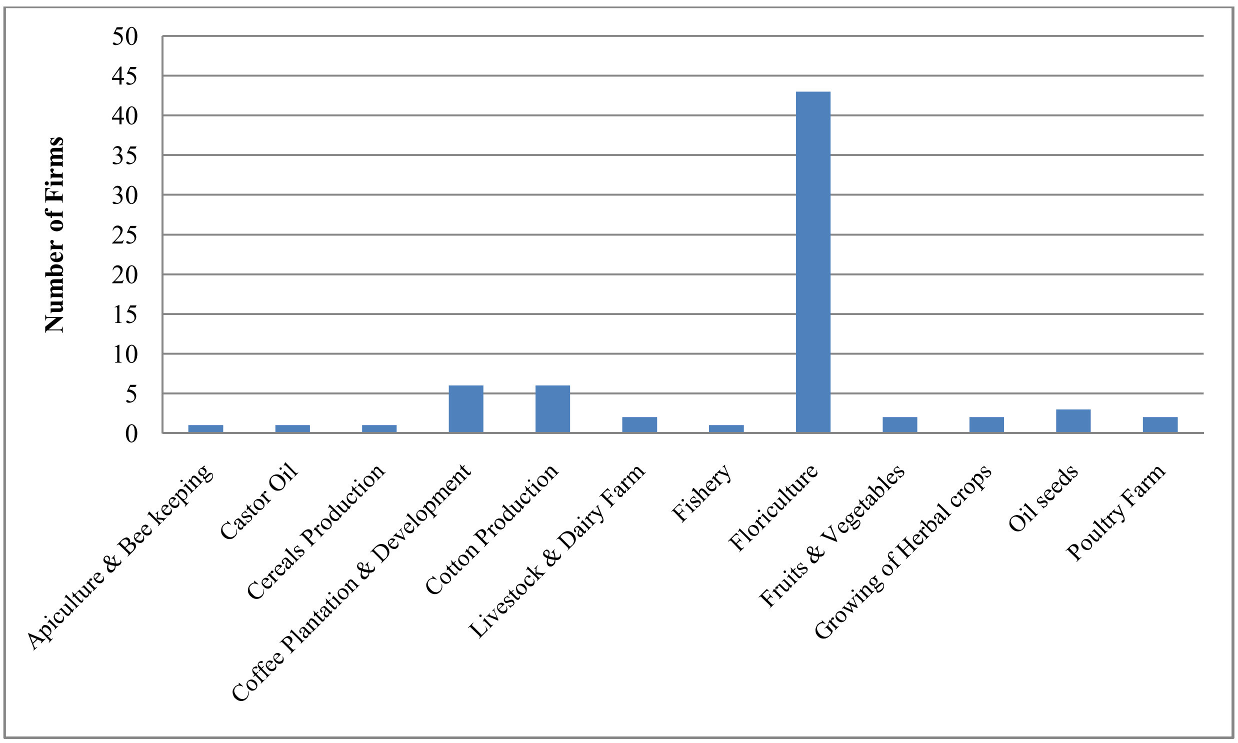


Figure 4: Farm Type and Number of Loans

Out of the total loans studied, loans granted to firms engaged in floriculture production are the highest by accounting for 61% followed by those who are engaged in coffee plantation and development and cotton production each accounting for 9% of the total loans. This indicates that the agricultural loan portfolio concentration of the bank is high for the floriculture industry. On the other hand, firms producing oil seeds which only accounted for 4% of the total loan. Nonetheless, firms involved in bee keeping, castor oil production, cereals production, livestock and dairy, fishery, fruits and vegetables, herbal crop production and poultry business all together accounts only for 17% of the total loans.

4.1.2. Outstanding Loan

Figure 5 illustrates the amount of total agricultural loan outstanding as at June 30, 2013. Total agricultural loan outstanding as at June 30, 2014 is birr 4.13 billion, of which 34% (birr 1.4 billion), 18% (birr 729.19 million) and 13% (birr 546.89 million) is loan disbursed to floriculture, cotton and coffee development farms respectively. The bank's loan exhibits high concentration in the floriculture sub-sector. This is a reflection of the high priority given by the government and the bank to the sub-sector. Loan disbursed to poultry farms represent the lowest share of the total agricultural loan outstanding in 2013 (birr 243.06 million). Cereal, livestock, fruits and vegetable and oil seeds production accounts for about 7% of the total outstanding each.

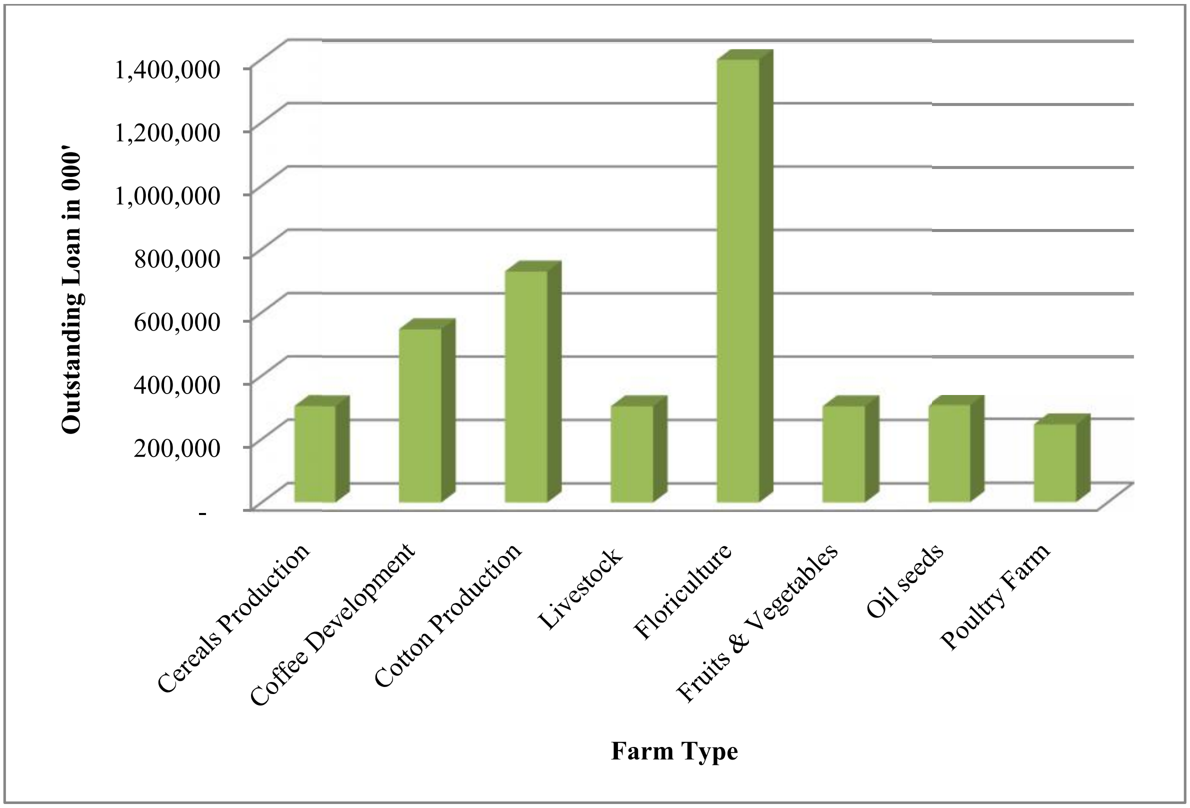


Figure 5: Loan Outstanding by Farm Type

4.1.3. Distribution of Loans by Number of Financial Statements

Figure 5 groups the studied firms according to the number of consecutive annual financial statement observations available for each firm. It shows the number of borrowers that have either one or multiple financial statement observations for different lengths of time. For about six firms, only one balance sheet belongs to the data set, while for the rest two to seven consecutive annual observations existed. The maximum seven consecutive annual financial statements were available for 13 firms. Multiple observations are important for evaluation of the extent to which trends in financial ratios help predict defaults (Hayden, 2002).

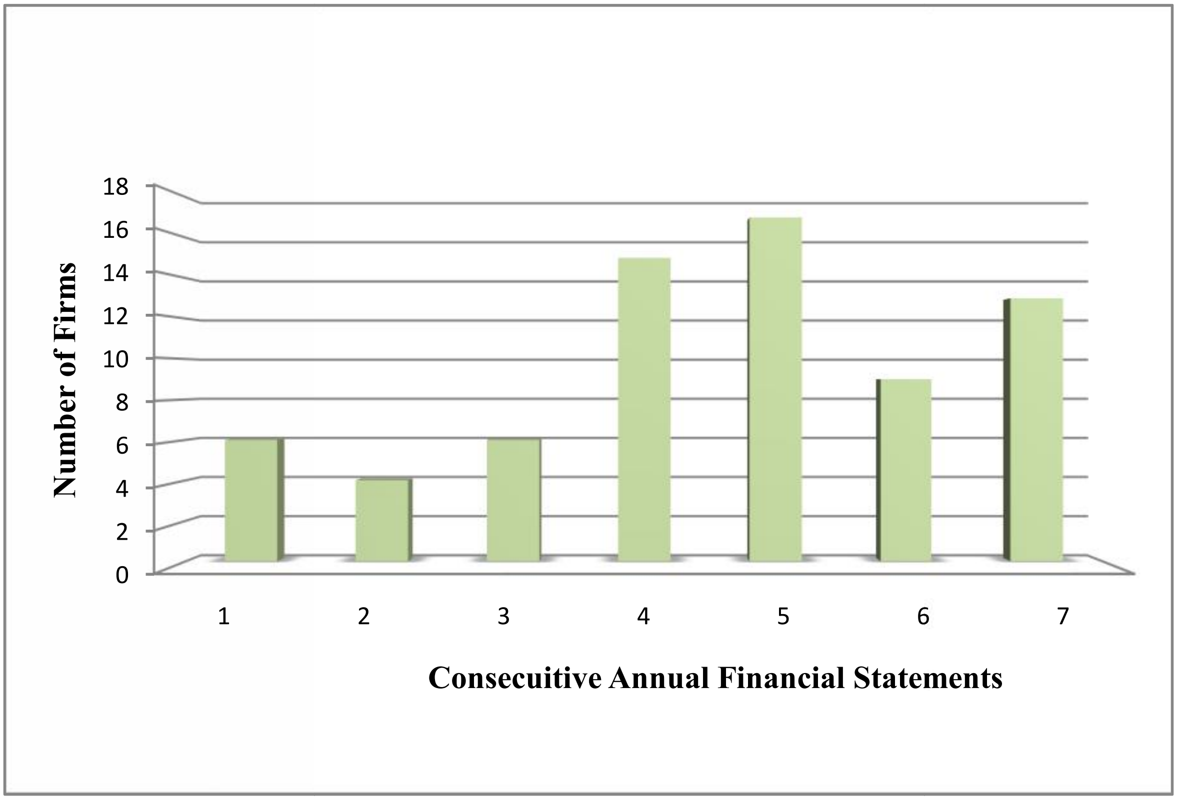


Figure 6: Number of Loans by Yearly Financial Statements

4.1.4. Statistics of Financial Variables

Table 1 presents the statistics of the explanatory variables for the total sample. Profitability variable has higher variation than debt coverage, leverage and liquidity. The loan duration varies from 1 year to a maximum of 10 years with average loan duration of 3.96 years. Loan size also varies from birr 1.02 million to birr 140.79 million with an average loan size of birr 29.08 million.

Table 1: Statistics of Financial Variables (Total)

Variables	Number	Minimum	Maximum	Mean	Std. Deviation
Leverage	322	0.0210	0.9850	0.3423	0.2357
Liquidity	322	0.0100	0.7120	0.2427	0.1431
Profitability	322	0.0490	7.2870	1.8298	1.2135
Debt Coverage	322	0.2330	8.1730	2.1471	1.1283
Loan Size	322	1,022,534	140,793,127	29,523,932	29,082,588
Loan Duration	322	1	10	3.96	1.86

4.1.5. Comparison of Default and Non default Loan Groups

To enable comparison of the characteristics of default and non default firms, separate statistics is shown in table 2 and table 3 below for each group. Numeric comparison of the default and non-default loan groups reveals that the mean for leverage is higher for the defaulted loans than the non-defaulted loans, which is consistent with our expectation. Firms financing their assets through higher debt are very likely to default. For liquidity, the mean value is higher for non-defaulted loans. Here, firms with sufficient working capital expand easily and generate sufficient fund that could enable them repay borrowed funds as per agreed terms.

Table 2: Statistics of Financial Variables (Non default Group)

Variables	Number	Minimum	Maximum	Mean	Std. Deviation
Leverage	257	0.0210	0.6260	0.2526	0.1345
Liquidity	257	0.0680	0.7120	0.2862	0.1245
Profitability	257	0.0490	7.2870	2.0359	1.2153
Debt Coverage	257	0.2330	8.1730	2.4034	1.1071
Loan Size	257	1,022,534	140,793,127	25,954,850	25,734,259
Loan Duration	257	1	10	3.81	1.84

Table 3: Statistics of Financial Variables (Default Group)

Financial Ratios	Number	Minimum	Maximum	Mean	Std. Deviation
Leverage	65	0.0490	0.9850	0.6969	0.2153
Liquidity	65	0.0100	0.3480	0.0708	0.0559
Profitability	65	0.0750	3.6310	1.0149	0.7961
Debt Coverage	65	0.5340	2.5840	1.1339	0.4197
Loan Size	65	1,070,357	128,164,774	43,635,535	36,603,151
Loan Duration	65	1	9	4.57	1.81

Also, as expected, the mean for profitability is higher for non-defaulted loans. The majority of companies generating higher profit are found to be non-default. Debt coverage has higher mean for non-defaulted loans as expected. The larger proportion of firms with higher debt coverage ratio is reported to be non-default.

Both loan size and loan duration have higher mean value for defaulted loans, indicating a negative relationship with default. The result suggests that, the higher the loan size and the longer the loan duration, the higher is the risk of default.

The coefficient of variation for leverage and loan size is higher for the defaulted loans, whereas the coefficient of variation for liquidity, profitability, debt coverage and loan duration is higher for the non defaulted loans. This means that, the extent of variability in relation to the mean, for leverage and loan size is high among the defaulted loans and for liquidity, profitability, debt coverage and loan duration is higher among the non default group.

4.2. Econometric Result

4.2.1. Default Model Estimation

To model agricultural loan default probability, binary logit model was used and the model was estimated by IBM SPSS Statistic 21 econometric software. The dependent variable of the model is loan default and the model utilizes seven independent variables; leverage, liquidity, profitability, debt coverage, loan size, loan duration and farm type. Most of the factors hypothesized to impact on the probability of default were found to be statistically significant with anticipated signs. The result showed that these variables at loan origination are good indicators of the probability of default.

Estimation results of the coefficients of the default model are tabulated in Table 4 below. The signs of the estimated coefficients for liquidity, profitability and debt coverage are negative as expected since an increase in these variables, ceteris paribus, decrease the default rate. As expected, the sign for the leverage variable is positive.

Table 4: Logistic Regression Results

Variables	Coefficient	S.E.	Wald	df	Sig.
Leverage	11.050	3.222	11.762	1	.001
Liquidity	-26.637	8.410	10.031	1	.002
Profitability	-1.233	.583	4.466	1	.035
Debt Coverage	-2.910	.958	9.225	1	.002
Loan Size	.000	.000	.019	1	.890
Loan Duration	-.060	.272	.049	1	.826
Cereal	2.479	3.015	.676	1	.411
Coffee	-1.746	2.413	.524	1	.469
Cotton	-.361	1.626	.049	1	.824
Livestock	.519	1.870	.077	1	.781
Floriculture	-.467	1.057	.196	1	.658
Fruit & Vegetable	1.043	1.504	.481	1	.488
Oil Seeds	-1.080	1.567	.475	1	.491
Poultry	.310	3.248	.009	1	.924
Constant	3.478	5.858	.352	1	.553

The Wald statistics and associated probability provide an index of the significance of each predictor in the model.

The hypothesis to test the significance of the coefficients is:

$$H_o: \quad \beta\text{'s} \quad = \quad 0$$

$$H_1: \quad \beta\text{'s} \quad \neq \quad 0$$

The Wald Statistic calculates the square of the ratio of the estimate to its standard error; $(b_i\text{'s}/S_{bi}\text{'s})^2$. It has a chi-square distribution and the simplest way to assess the Wald statistic is to take the significant values and if it is less than 0.05, at 95% confidence level, reject the null hypothesis as the variables do make a significant contribution. In our case, the leverage, liquidity, profitability and debt coverage variables contribute significantly to the default model as their significance value is less than 0.05.

From table 4 we can see that the final default model contains four accounting ratios and takes the following forms:

$$\begin{aligned} \textit{Log Odds} = PD/(1 - PD) = 3.478 &+ 11.05 * \textit{Leverage} \\ &- 26.637 * \textit{Liquidity} \\ &- 1.233 * \textit{Profitability} \\ &- 2.91 * \textit{Debt Coverage} \end{aligned}$$

4.2.2. Model Fitness Test

The simplest tool to indicate how good the model is at predicting the outcome variable is to produce a classification table as presented in table 5 below. Of the 257 cases observed as non-default, the model correctly predicted 253 cases, i.e. they have fitted probability of less than 0.5. Similarly, of the 65 cases observed as default, the model correctly predicted 62 cases, i.e. they have a fitted probability of greater than 0.5. Generally, the higher the overall percentage prediction, which is about 97.8% in our case, the better is the model.

Table 5: Proportion of Cases Correctly Classified by the Model

Observed	Predicted		
	Non-Default	Default	Percentage Correct
Non-Default	253	4	98.4
Default	3	62	95.4
Overall Percentage			97.8

The sensitivity of the model is the percentage of the group that has the characteristic of interest, default in our case, which has been accurately identified by the model. The model is able to correctly predict 95.4% of the loan which did default. On the other hand, the specificity of the model is the percentage of the group without the characteristic of interest, non-default in our case, which is correctly identified. The specificity is 98.4%, which are non-defaulted loans correctly predicted by the model.

Another statistical test employed to check the overall significance of the model fit is the model chi-square. It is a test used to see whether inclusion of explanatory variables in the model tells us more about the outcome variable than the model that does not include the explanatory variables. The model chi-square is derived from the likelihood of observing the actual data under the assumption that the model that has been fitted is accurate. The hypothesis to test in relation to the overall fit of the model is:

***H_o*: the model is a good fitting model.**

***H_1*: the model is not a good fitting model.**

Model chi-square is also known as likelihood ratio test which is based on what is called likelihood function. Test for model chi-square is based on this statistic which measures the degree of discrepancy between the observed and predicted values from the model. The difference between -2LL (-2*log-likelihood) for the best fitting model and -2LL (-2*log-likelihood) for the null hypothesis model in which all the coefficients are set to zero is distributed like chi-squared with degrees of freedom equal to the number of predictors. In our model, the chi-square has 4 degrees of freedom, a value of 288.123 and a probability of, p < 0.000 (See table 6 below). Thus the indication is that the model has a poor fit, with the model containing only the constant indicating that the predictors do have a significant effect and create essentially a different model.

Table 6: Model Chi-square Statistic

Description	Chi-square	df	Sig.
Step	288.123	14	0.000
Block	288.123	14	0.000
Model	288.123	14	0.000

An alternative to model chi-square to test the overall fitness of the model is the Hosmer and Lemeshow test which divides subjects in to 10 ordered groups and then compares the numbers actually observed in each group to the number predicted by the logistic regression model. The groups were formed based on their estimated probability, those with estimated probability below 0.1 from one group and so on up to those with probability of 0.9 to 1.0. The difference between the observed number and the expected number, calculated by summing predicted probabilities based on the model, in each group were then assessed using a chi-square test. The goodness of fit statistic is then calculated as:

$$\sum \frac{(O - E\,)2)}{E}$$

Where, *O* and *E* are the observed and expected numbers in a cell. The closer the expected numbers are to the observed, then the smaller the value of this statistic. Small value indicates that the model is a good fit. The value of this statistic is 6.981 and the p-value is 0.539. Thus, we do not reject the null hypothesis that there is no difference between the observed and the predicted values. The model appears to fit the data very well.

An approximate measure to the coefficient of determination for logistic regression, R^2, which is a measure of the proportion of variation explained by the model, is given by Cox & Snell R Square and Nagelkerke's R Square (See table 7). Cox & Snell R Square attempts to imitate multiple R-Square based on likelihood, but its maximum can be (and usually) is less than 1.0 making it difficult to interpret. In the estimated model, it is indicating that 59.1% of the variation in the dependent variable is explained by the logistic model. Nagelkerke's R Square is a modification over the former test and its measure ranges from 0 to 1. For the model, it is 0.932, indicating a strong relationship of 93.2% between the predictors and the dependent variable, default.

Table 7: Measure of Variations Explained by the Model

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
35.792	0.591	0.932

Liquidity is found to have negative relationship with loan default. This is consistent with the finding of Katchova and Barry (2005). They found that liquidity in personal assets highly significant and have a negative relation with default. Companies that have more working capital may be more successful since they can expand quickly with internal resources. Companies with low working capital may lack the funds necessary for growth and hence, poor repayment performance.

The profitability variable is also significant indicator of default with negative relationship. Katchova and Barry (2005), studied the profitability variable and found similar result. Similarly, in 2001 Gallagher found credit assessment models and predicted that financial ratios such as leverage, liquidity and profitability a significant indicator of loan default. Companies generating sufficient funds are expected to be creditworthy and less likely to default.

Debt coverage ratio is significant and has negative relationship with loan default. Firms earning higher income before tax and interest expense in relation to interest expense are less likely to default. Conversely, the higher the amount of debt, the higher the amount of bank interest rate so that firms are likely to default. The result is consistent with the findings of Featherstone and Boessen, (1994).

As expected, the sign for the leverage variable is positive. Firms with a high debt ratio are said to be highly leveraged and hence they are more likely to default as the owners' equity contribution is lower. Similar studies and theories also suggest the same relationship.

Loan size was hypothesized to have either positive or negative relationship with agricultural loan default. Katchova and Barry (2005), examined if loan size explains agricultural loan default. In their result, loan size did not appear to be a very important factor influencing loan default. Borrowers with larger amount borrowed were more likely to default, though the level of significance did not reach the 5 percent threshold.

In the present study, all origination ratios were statistically significant at the 95% level and their signs were as expected. However, loan size did not appear to be a very important factor in influencing loan default. The coefficient estimate of loan size is not statistically different from zero. Thus, loan size did not have a statistically significant impact on probability of default. The result suggests that it is may be the relation between farm size and loan size that influences default probability. Larger loan amounts do not necessarily increase default risk as long as a large loan amount is consistent with a larger farm size. This is similar to the findings of Featherstone and Barry (2002).

The variable loan duration was also examined if loans having longer duration lead to increase in the probability of default. The duration of the loan was computed by calculating the number of years between the origination date and the maturity date of the loan. The intuition for the expected sign is that the longer the loan duration, the lower the amount of principal repaid, the higher the risk of default. The outcome of the regression indicated that all the origination ratios are statistically significant at the 95% level and have the expected signs. However, the coefficient of loan duration was not statistically significant and loan duration has no significant impact on loan default.

Specialization in production of a certain commodities was indicated to be one of default indicators. It is tested if this variable has any predictive power on default. It was included in the analysis as a dummy variable and the regression result shows that the farm type was not found to be a significant predictor of default. However, farms specializing in cereal, coffee and fruits and vegetables production were found to be less likely to default as compared to other farm types. The default probability in poultry and cotton production is very high.

4.2.3. Effect of Change of Variables on Probability of Default

To interpret the meaning of the coefficients, further computations need to be made. For a binary logit model, the impact of a one-unit increase of the independent variable, other explanatory variables held constant, is not the probability of default itself. The estimated logistic coefficients are used to create a default probability prediction equation.

The probability of default (P_i) is given by:

$$P_i = f(b.xi) = e^{bxi} \Big/ 1 + e^{bxi}$$

Where: b_i*'s:* *are the estimated coefficients and*

x_i*'s:* *are the independent variables.*

To estimate the effect on the probability of default of change of one variable when the other three variables are held constant, the means for three of the variables were multiplied by their coefficients while one of the variables multiplied by the coefficient was varied. The effect is evaluated between two standard deviations below and above the mean of the variable of interest.

Figure 7 represents the probability of default as the leverage variable varies, the other three held constant. As leverage increases from 0.1 to 1, while liquidity, profitability and debt coverage held constant, the probability of default increases from 0.01% to 15.78%. On the other hand, as the liquidity variable increased from 0.01 to 0.9, the probability of default decreased from 18.09% to 2.56% (Figure 8). This is consistent with our expectation of decrease in the probability of default with increase in liquidity variable. Also as expected, increase in the value of profitability leads to a reduction in default probability. As profitability increased from -0.05 to 1.0, the probability of default decreased from 0.45% to 0.12% (Figure 9). Similarly, an increase in debt coverage variable leads to a decrease in probability of default as presented in Figure 10. As debt coverage increases from -0.1 to 1.0, while the other variables are held constant, the probability of default decreases from 23.69% to 1.25%.

V. SUMMARY, CONCLUSION AND RECOMMENDATION

5.1. Summary

Close observation of the banking industry shows that bankers and regulators have given due attention to credit risk modeling and it has become a key component in bank management. Recently, the topic has drawn the attention of many scholars. Agricultural lenders also need to pay attention to the new regulations as an agricultural loan is assumed to be risky than industry and service loans. However, credit risk models for agricultural loan portfolios are still in their infancy, calling for further investigation.

The objective of this study was to develop a credit risk model for agricultural loan portfolios. The objective was accomplished by conceptualizing a theory of loan default for agricultural borrowers and deriving a quantitative model predictive of loan default. The derived default probability model is applicable to agricultural loans which could be used by agricultural lending banks as a benchmark when setting their internal rating models.

The main testable hypotheses were based on loan origination financial ratios. Financial ratios available at loan origination time were used as the main inputs to the statistical analysis based on logistic regressions. Besides, loan size, loan duration and farm type were included into the model building process, though they were not statistically significant in explaining default.

The results of the binomial logit model applied to origination loan origination data from the Development Bank of Ethiopia indicated a strong and direct relationship between the financial variables and default. The regression output demonstrated that four origination variables are important predictors of probability of default of agricultural loan portfolio: leverage, liquidity, profitability and debt coverage. These variables were good in explaining the default rate and the coefficients were statistically significant and consistent with the underlying theory. The default model explains more than 95% of variability of the default rate. The loan size, loan duration and farm type however, were not statistically significant in predicting the probability of default.

Leverage as measured by total liability divided by total asset was found to be statistically significant in explaining agricultural loan default. Highly leveraged borrowers were found to be more likely to default and company's financing their assets by higher equity are less likely to default. Liquidity defined as working capital divided by total assets was also indicated to be a strong default indicator. Companies that have more working capital are more successful as they can expand quickly with internal resources and able to repay their debt obligation in time. Likewise, profitability, ratio of net income to total asset was also found significant in explaining default. The higher the profitability ratio is the lower the default probability. Debt coverage ratio was also examined if it had relation with default. It is a ratio between income before interest and tax and interest expense. The variable had strong relation with default and their relation is negative.

5.2. Conclusion

The default model developed in this study has several advantages for bankers and regulators and has implications for further study. The applicability of a default model for banks is becoming a prerequisite. This model can provide valuable credit risk management variables, the probability of default. This information can be used for the internal management of a bank as well as for oversight reasons by regulators.

The result of the binomial logit model could enable an identification of borrowers in greatest need of special attention. Regulators also expressed their concern on the importance of a better segregation of customers as a potential for increased risk sensitivity. Thus, depending on such models, banks can provide special service required to help avoid default among those borrowers considered more likely to default. By developing default predictive models, banks would be able to measure portfolio risk, price loans and improve their internal risk management at the same time. Banks could benefit from lower capital requirements and would better rate the default risk.

The research was based on the analysis of agricultural loan data set supplied by Development Bank of Ethiopia. The data set was carefully inspected and checked for linearity and data integrity. However, there is still a room to upgrade the methodology by applying to out of sample data set and testing the accuracy of the model using different statistical methods. Therefore, an agricultural lender interested in the model would be required to develop a robust data base and loan segmentation process based on commodity type.

5.3. Recommendation

- ☞ The regression analysis indicates that companies that have more working capital are more successful as they can expand quickly with internal resources and those with insufficient working capital lack the funds necessary for growth, which increase probability of agricultural loan default. Thus, while availing credit to agricultural firms, DBE has to ensure that there is sufficient working capital fund to enhance growth of companies.

- ☞ Firms with larger debt proportion as compared to total assets employed were more likely to default. Firms with higher equity investment are less likely to default. Equity contributions of firms play a significant role in loan repayment performance of agricultural firms. Therefore, the bank has to keep the debt-equity ratio flexible and has to treat borrowers with different debt-equity ratio depending on firms' capacity to raise equity capital.

- ☞ One of the implications of this study is that, agricultural loans default is closely related to firm's net cash flow. Consideration of the cash flow effect in credit risk modeling is important in agricultural loan since most agricultural activities have seasonal cash flows. DBE has to develop separate default model for its agricultural loans that takes in to account the characteristics unique to the agricultural sector based on the cash flow of agricultural firms.

- ☞ By applying default probability model, DBE can forecast the associated default risk with every individual loan. Thus, using default probability model, DBE has to differentiate loan price over loans having different risk level and should determine risk based capital requirements.

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APPENDIX

Table 8: Credit Risk Grading System of DBE

Pre-credit Risk Grading

Expected Risk	Assigned Points
A. Business/Applicant Strength (Critical issue) • Character of the Applicant	35
• Project Management Risk	25
• Capital Adequacy Risk	20
• Market Risk	20
Total	**100**
B. Collateral/Guarantee Strength (Last resort)	

Post-credit Risk Grading

Risk Type	Assigned Points
A. Project/Business Assessment (First Option) • Default Risk • Character of the Borrower • Project Management Risk • Market Risk • Capital Adequacy Risk	 30 25 20 15 10
Total	**100**
B. Collateral/Guarantee strength (Last resort)	

Risk Rating Points of DBE

Grade Interval	Security Strength
x≥150%	Strongly secured
125%≤x<150%	Fully secured
100%≤x<125%	Partially secured with a moderate risk
75%≤x<100%	Partially secured with a high risk
x<75	Unsecured

Linearity Test for Liquidity, Profitability and Debt Coverage, Ratios

This figures show the relationships between the variable liquidity, profitability and debt coverage ratios and the empirical log odd, which is derived by dividing the ratios into about 14 groups and calculating the historical default rates respectively, the empirical log odd within each group. Finally a linear regression of the log odd on the mean values of the variable intervals is estimated and depicted, too. We can see that for these variables, the linearity assumption is valid.

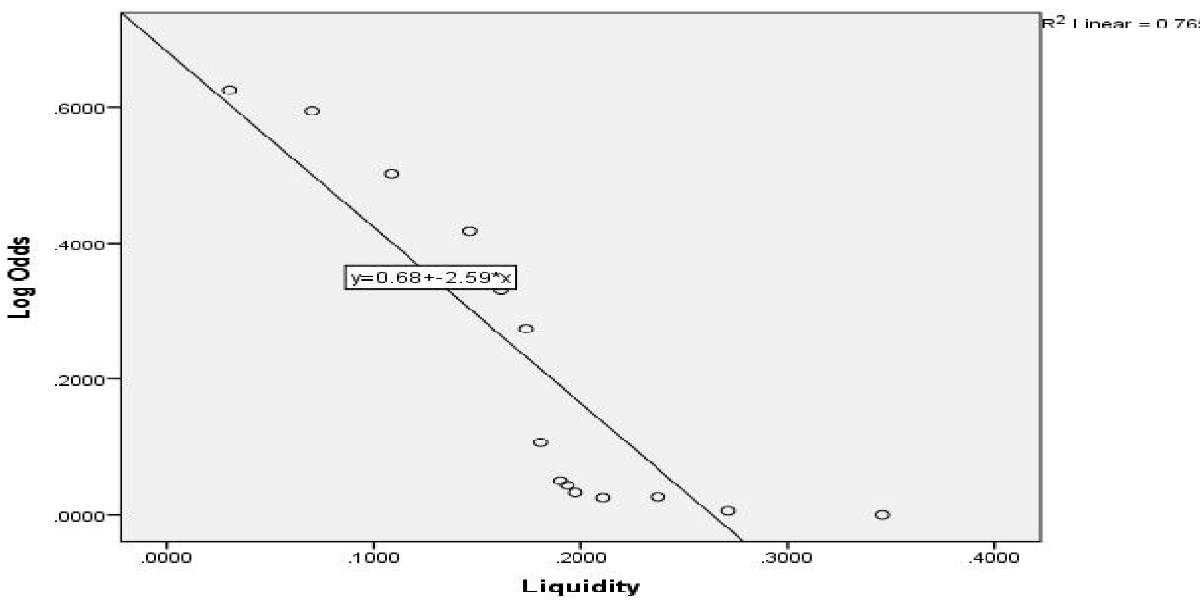
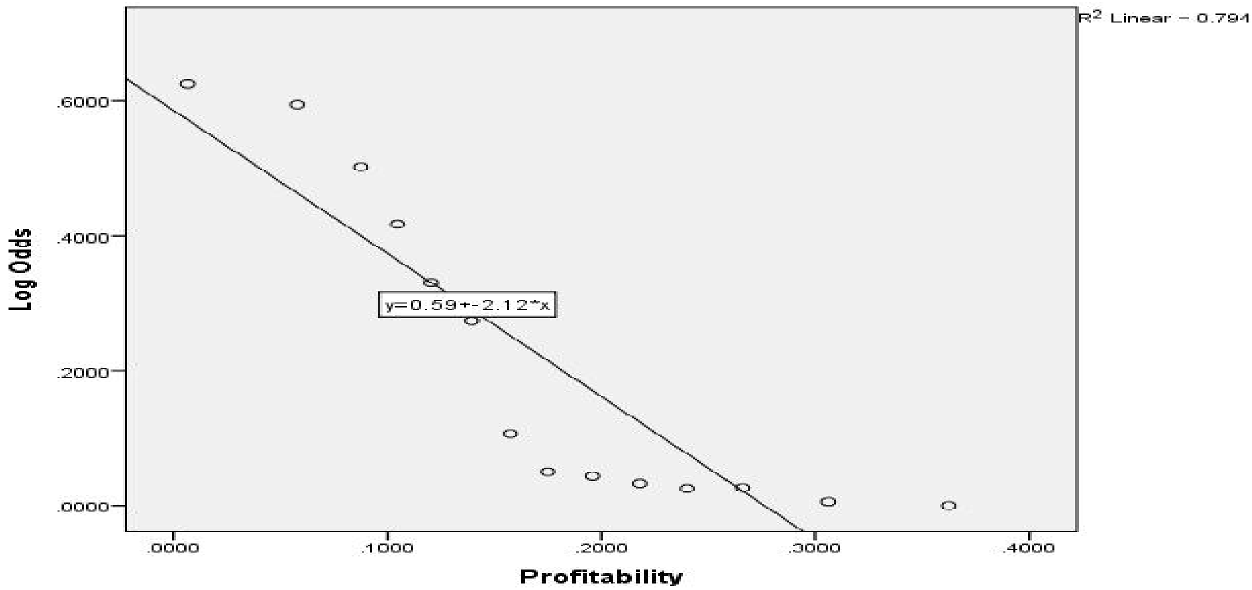
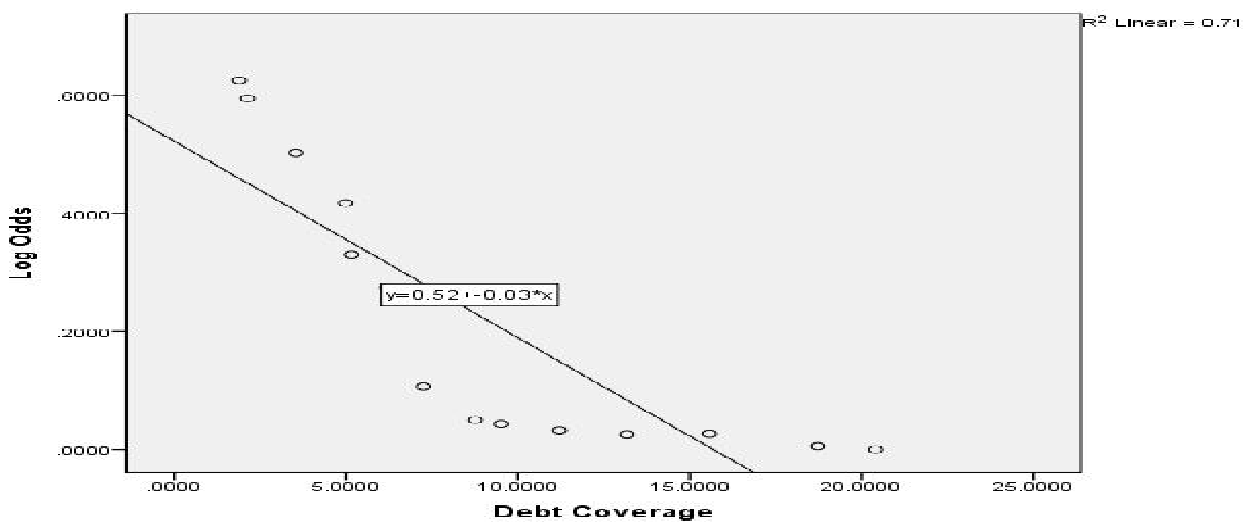


Figure 7: Linearity Test for Liquidity, Profitability and Debt Coverage, Ratios



R2 Linear = 0.794
Log Odds
.6000
.4000
.2000
.0000
y=0.59+-2.12*x
.0000
.1000
.2000
.3000
.4000
Profitability



R2 Linear = 0.711
Log Odds
.6000
.4000
.2000
.0000
y=0.52+-0.03*x
.0000
5.0000
10.0000
15.0000
20.0000
25.0000
Debt Coverage

Probability of Default as Leverage Varies, Keeping Others Constant

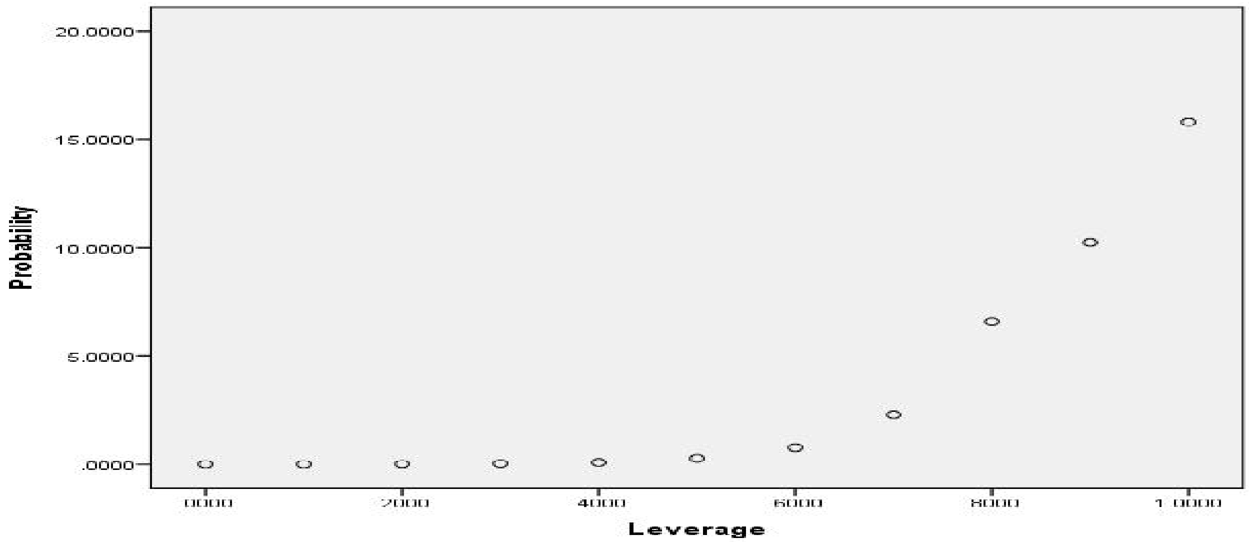


Figure 8: Probability of Default as Leverage Varies, Keeping Others Constant

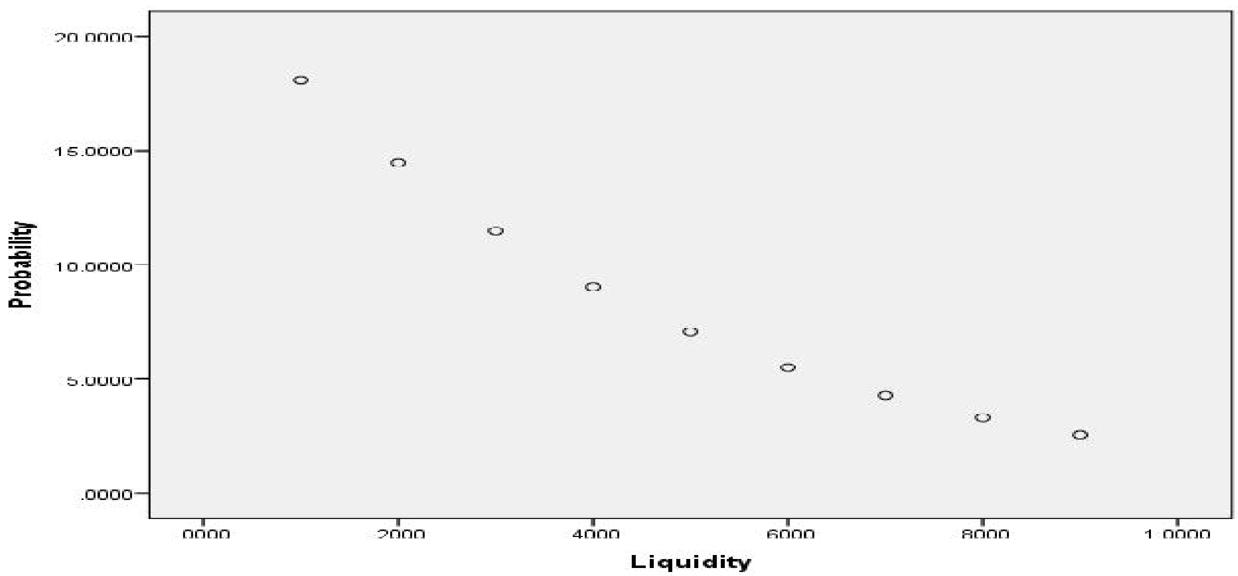


Figure 9: Probability of Default as Liquidity Varies, Keeping Others Constant

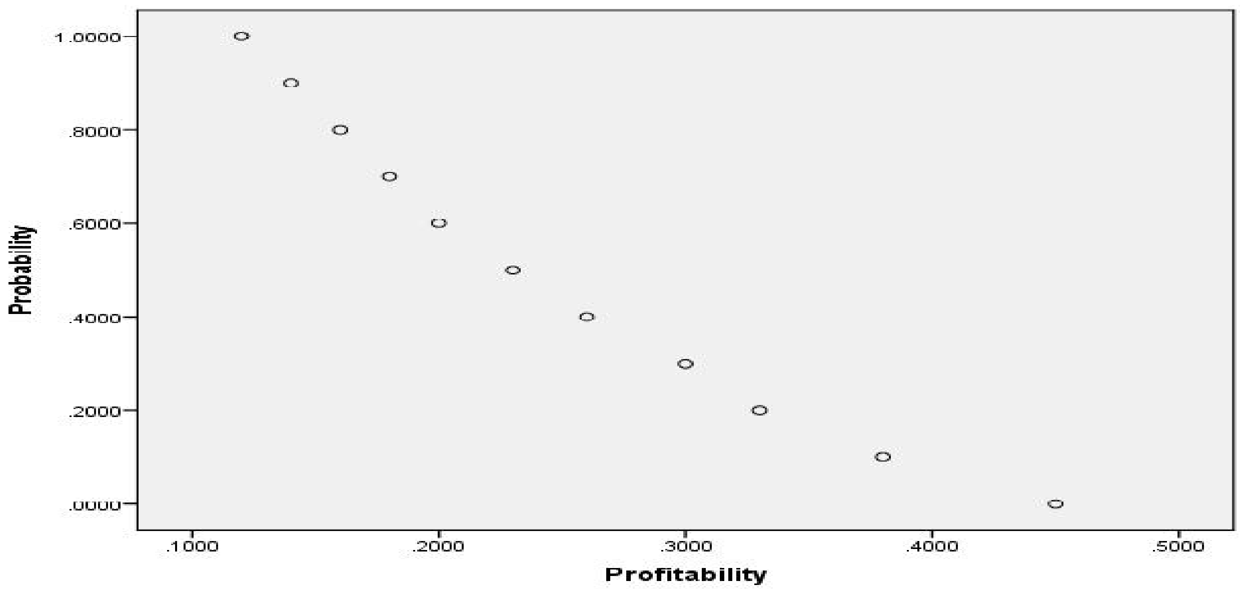


Figure 10: Probability of Default as Profitability Varies, Keeping Others Constant

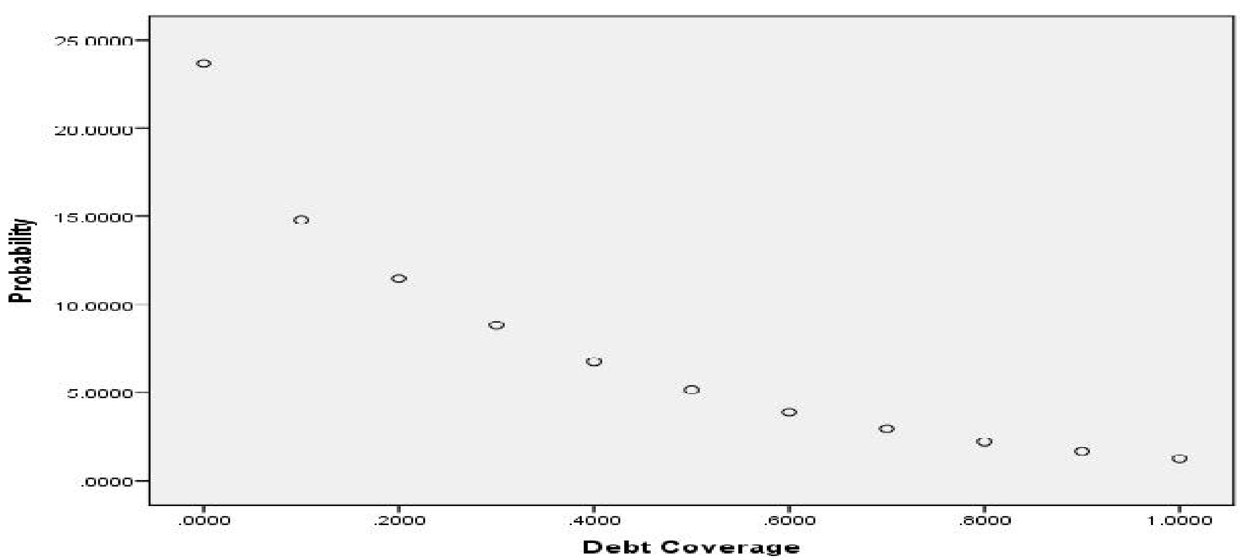


Figure 11: Probability of Default as Debt Coverage Varies, Keeping Others Constant

Logistic Regression Outputs

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	322	100.0
	Missing Cases	0	.0
	Total	322	100.0
Unselected Cases		0	.0
Total		322	100.0

Dependent Variable Encoding

Original Value	Internal Value
Non-Default	0
Default	1

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted		
			Default		Percentage Correct
			Non-Default	Default	
Step 0	Default	Non-Default	257	0	100.0
		Default	65	0	.0
	Overall Percentage				79.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.375	.139	98.039	1	.000	.253

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	LEVER	184.846	1	.000
		LIQUI	117.862	1	.000
		PROFI	36.836	1	.000
		DCOVE	65.877	1	.000
		LONSI	19.234	1	.000
		LOLE	8.791	1	.003
		CEREAL(1)	.459	1	.498
		COFFEE(1)	.980	1	.322
		COTTON(1)	.013	1	.910
		LIVEST(1)	.226	1	.635
		FLORIC(1)	.087	1	.769
		FRUIT(1)	.763	1	.383
		OILSEED(1)	.809	1	.369
		POULT(1)	.405	1	.525

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	288.123	14	.000
	Block	288.123	14	.000
	Model	288.123	14	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	35.792[a]	.591	.932

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.981	8	.539

Contingency Table for Hosmer and Lemeshow Test

		Default = Non-Default		Default = Default		Total
		Observed	Expected	Observed	Expected	
Step 1	1	32	32.000	0	.000	32
	2	32	32.000	0	.000	32
	3	32	32.000	0	.000	32
	4	32	31.999	0	.001	32
	5	32	31.996	0	.004	32
	6	32	31.976	0	.024	32
	7	31	31.882	1	.118	32
	8	30	29.099	2	2.901	32
	9	4	4.004	28	27.996	32
	10	0	.043	34	33.957	34

Classification Table[a]

	Observed		Predicted		
			Default		Percentage Correct
			Non-Default	Default	
Step 1	Default	Non-Default	253	4	98.4
		Default	3	62	95.4
	Overall Percentage				97.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	LEVER	11.050	3.222	11.762	1	.001	62924.895
	LIQUI	-26.637	8.410	10.031	1	.002	.000
	PROFI	-1.233	.583	4.466	1	.035	.291
	DCOVE	-2.910	.958	9.225	1	.002	.054
	LONSI	.000	.000	.019	1	.890	1.000
	LOLE	-.060	.272	.049	1	.826	.942
	CEREAL(1)	2.479	3.015	.676	1	.411	11.934
	COFFEE(1)	-1.746	2.413	.524	1	.469	.174
	COTTON(1)	-.361	1.626	.049	1	.824	.697
	LIVEST(1)	.519	1.870	.077	1	.781	1.680
	FLORIC(1)	-.467	1.057	.196	1	.658	.627
	FRUIT(1)	1.043	1.504	.481	1	.488	2.839
	OILSEED(1)	-1.080	1.567	.475	1	.491	.340
	POULT(1)	.310	3.248	.009	1	.924	1.363
	Constant	3.478	5.858	.352	1	.553	32.392