St. MERRY'S UNIVERSITY
SCHOOL OF GRADUATE STUDIES
MASTER OF BUSINESS ADMINISTRATION

BASELINE BANK FAILURE PREDICTION MODEL FOR THE ETHIOPIAN BANKING INDUSTRY: USING LOGISTIC REGRESSION MODEL

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DECLARATION

I, **Yisehak Abreham T/Tsion**, hereby declare that the thesis work entitled "**BASELINE BANK FAILURE PREDICTION MODEL FOR THE ETHIOPIAN BANKING INDUSTRY: USING LOGISTIC REGRESSION MODEL**" submitted in partial fulfillment of the requirements for Master of Business Administration (MBA) to St. Merry University School of Graduates, is the outcome of my own effort and that all sources of materials used for the study have been duly acknowledged.

This study has not been submitted for any degree in this University or any other University.

Name ***Yisehak Abreham***

Signature ___________________________

Date_______________________________

Acknowledgments

Finishing this thesis took much longer than I ever anticipated and I am happy that finally the long and painful process is over.

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And to Mr. Warren Buffet, an investment guru and respected businessmen, for his inspirational quote **“It’s only when the tide goes out that you learn who’s been swimming naked.”** which inspired me to write my master thesis on bank failure prediction model.

In memory of my father!

To my mother

With love and eternal appreciation!

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Abbreviations and Acronyms

WTO	World Trade Organization
M2	Money Supply
GDP	Gross Domestic Product
FDIC	Federal Deposit Insurance Corporation of U.S.
SDIF	Savings Deposit Insurance Fund of Turkey
WB	World Bank
EWS	Early Warning Signal
CAMEL	Capital Adequacy, Asset Quality, Management, Earning & Liquidity
U.S.	United States of America

Abstract

Failure of a bank and a systemic crisis in one country can easily spill over into other countries and develop into a global crisis. So developing early warning signal models capable of identifying banks with high and increasing failure probabilities ahead of time has a prime importance in preventing or minimizing losses. To develop bank failure prediction model for Ethiopia, the researcher believes that, we don't have to wait for actual failure to happen. Instead failure situation in other countries can provide us a useful benchmark to easily identify Ethiopian banks with high and increasing probabilities of failure proactively. Against this backdrop, the intent of this paper is to develop baseline bank failure prediction model for the Ethiopian banking industry that might help to prevent any bank failure and financial crises in the future using cross-country experience. The study used banks from Ethiopian, Turkish and U.S. The study was based on secondary data which was collected from the published annual reports of the respective banks. The data are taken on the annual basis from 2008/09 to 2013/14 for Ethiopian banks and from 1997 to 2000 for Turkey banks and from 2008 to 2014 for U.S. banks. The researcher tried to predict financial failure in these banks one year ahead of financial failure date. For this reason, failed banks' balance sheets and income statements from the period one year prior to failure are used. The researcher used bank specific 19 financial ratios that are calculated from the financial statements of the respective banks as explanatory variables.

The study begins with an exhaustive literature review with the purpose of understanding well the topic of bank failure prediction. Most of the models and techniques of failure prediction modeling up to this date are covered here. In analyzing the quantitative data, the study used logistic regression model to ascertain the effects of CAMEL ratios on the likelihood of bank failure. The cross-country suggest that the variables C1 (capital adequacy), E1 (earning), M2 (management), and L1 (liquidity) are statistically significant in predicting bank failure. The cross-country bank failure prediction model displays high percentage of outcomes to be correctly classified, good goodness-of-fit and high specificity. The overall predictability accuracy of the logistic regression model was 92%. The derived cross-country baseline logit model is:

Ln [Probability of Failure/

Probability of Non-failure] = -.25 - .507(C_1) + .327(M_2) - .830(E_1) - .093 (L_1)

Keywords: *bank failure, logistic regression, CAMEL ratios, early warning signal.*

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Chapter I

1. Introduction

1.1. Background of the Study

Banks play a vital role in the efficient allocation of resources of countries by mobilizing same for productive activities. Hence banks occupy strategic position in promoting the growth and development of any economy (Ikpefan et al, 2014). Banking is all about leverage. That is, banks are by far highly leveraged institutions than any other industry or service sectors. Banks fund large portion of their assets with borrowings (by mobilizing deposits) rather than equity (raising capital). Beyond a certain point, however, too much leverage can be fatal. Especially in the time of systematic distress and macroeconomic volatility, banks may run shortfall in servicing debt leading them to collapse (Tsatsaronis et al, 2012). Thus, if one bank fails, unlike other sectors, it merely constitutes an individual problem (Caprio et al, 2006). The impact of failure in the banking sector can easily affects the economy as a whole.

The most obvious indicators that can be used to predict banking crises are those that relate directly to the soundness of the banking system (Hardy et al, 1998). Financial crises are not new. In the past two decades, developing and developed countries have been experiencing a wave of systemic financial crises. The notable ones are the financial crises in Mexico, Turkey, and Venezuela in 1994, Argentina in 1995, the five East Asian crisis economies, namely Indonesia, Korea, Thailand, Malaysia, and the in 1997, Russia and Argentina in 1998 and gain in Turkey in 2000 (Ghosh, 2006). Briefly, the fundamental factors that induced the crises are largely attributable to heavy short term foreign currency denominated borrowing from banks in other countries, capital outflows by creditors and sudden reversal in interest rates, devaluation of local currency and commodity prices, which cascade into a financial panic and result in an unnecessarily deep contraction (Claessens, 2013).

The latest financial crisis that flared up in September 2007 with the collapse of Lehman Brothers Holdings Inc., which filed one of the biggest bankruptcy in history; Merrill Lynch & Co., which announced an emergency sale to Bank of America Corp and the Federal Reserve takeover of American International Group Inc. to stave off a global financial turmoil have led to the collapse of numerous banks and other financial institutions and widespread repercussion on the wider economy (Bloomberg, 2008). What started as a financial crisis in the United States has snowballed into an economic crisis and further created a domino effect across the globe (Lin et al, 2012).

Though the world economy came out of the protracted recession the way in which the patterns of systemic financial failure have recurred around the world in the past years gives cause for concern that the current wave of crises may not yet be drawing to a close, and that it may soon be succeeded by another wave (Furman et al, 2010). What the history of the financial crisis has revealed convincingly is that the failure of a bank and a systemic crisis in one country can easily spill over into other countries and develop into a global crisis (Singer et al, 2007). Thus, financial disruption has highlighted the important for taking timely intervention and remedial measures for protecting bank failure: when problems are identified late, solving them is much more costly (Čihák et al, 2007). Unfortunately, in developing countries where there is lack of well-developed domestic capital markets and access to international capital markets makes the banking sector omnipresent and, therefore, any bank failures would have serious contagious repercussions in such economies (Moyo, 2014).

To sum up, impacts of failure in the banking sector can easily affects the economy as a whole. Bank failure could bring about dreadful impact on the banking system and a wide ranging ramification on the whole economy at large. It is in this light that the prediction of a potential bank failure that is capable of identifying potentially troubled banks earlier found to be pertinent to generate an early warning signal.

Developing an early warning system capable of identifying banks with high and increasing failure probabilities ahead of time for the Ethiopian banking industry is what this study tries to address.

1.2. Statement of the Problem

Banks are the most leveraged industry of any economy, so stability and soundness is an important parameter in the banking system. If one bank fails, it merely constitutes an individual problem to its depositors. By the very terms of the prophecy itself an insolvent bank will create a threat to financial stability resulting bank runs. Undoubtedly the failure of one bank will induce depositors to panic and run on other banks that do not, in fact, have an underlying solvency problem. This will weaken banks' capital base to a point where it cannot serve its liabilities. Such failure will underscores public confidence in the system and will result in massive withdrawal of deposits (Aghion et al, 2000).

Because of these regulatory bodies are intended to identify and address problems as they emerge, to avert failure when possible, and to make failures less costly when they do occur. Thus, it is apparent that the regulatory body has a considerable interest in regulating banks. It is essential to identify factors that may contribute to bank failure so that banks can take measures to eliminate the risk. By identifying problems early, regulators are able to force corrective action, or close the institution in a manner that minimizes losses to depositors and the deposit-insurance fund, and that minimizes the disruptive impact on the economy (Whalen et al, 1998).

When we come to our Country, the ever increasing globalization appears to have forged challenges inasmuch as it has brought about opportunities. That is, globalization has facilitated rapid exchange of international trade and services. However, this opportune could have own chain of reaction of failures to Ethiopia banks by gravitating into another country associated with trade relation. More than ever the Ethiopian economy has integrated to the world, thus impact on other country will have a commensurate impact in our country. The south-east Asian crisis and the recent global crisis is a case in point. The manifested crises negatively impacted our export commodities price and export earnings (Hussain et al, 1999 & Paul, 2010). Furthermore, the move by the Ethiopian government by selling ten years debt Eurobond worth USD 1 billion marked the integration of the economy to the international capital market. Any interest rate volatility will have immediate impact on the Bond's rate.

Liberalization of trade in financial sector is one aspect of the trend toward joining WTO. Acceding countries to the WTO have committed to opening up trade in financial services as part of their accession packages (Vander et al, 2004). In this case, Ethiopia government is interesting to be members of WTO. Thus, Ethiopia's commitment in this respect is inevitable. Financial institutions are thus expected to face stiff competition from foreign financial institution due to liberalization of the financial sectors. Several studies indicate that financial liberalization coupled with different institutional and macroeconomic factors is likely to precede banking crisis in developing and emerging countries (Hanson et al, 1990, Demirgüç-Kunt, 1998 & Arestis et al, 2006).

The banking industry of Ethiopia represents by far the most important segment of financial intermediation. There is hardly any industry which has benefited as much from the prolonged buoyant economic growth as the financial industry. Enhanced economic monetization has unleashed the potential of what has for long been an asset based economy as evidenced by the improvement in the M2/ GDP ratio, which rose from 16.08 percent in 1981 to 33.98 percent at the end of 2008 according to data from WB. Above all, restriction of foreign banking entry, low level of financial penetration, a stable exchange rate regime, and heavy capital restriction for establishing a bank, gave the existing financial industry unprecedented level of privilege.

Despite the good overall performance of banks in Ethiopia, bank failure in the foreseeable future might be imminent considering the ever increasing integration to the world economy and the possibility of Ethiopia’s accession to WTO. In Ethiopia where the financial sector is dominated by commercial banks, any bank failure in the sector has an immense implication on the performance of the economy. This is due to the fact that any bankruptcy that could happen in the sector has a contagion effect that can lead to bank runs, crises and bring overall financial and economic troubles. So, developing knowledge about bank failure in Ethiopia is deemed highly desirable in order to forestall very costly banking crisis outcomes.

So far, no one has attempted a study that undertaken on developing an early warning bank failure prediction model for the Ethiopian banking sector. Therefore, the major gap of this investigation wishes to fill it is by developing an early warning signal model for Ethiopia bank industry. To develop bank failure prediction model we don’t have to wait for actual failure to happen. Instead failure situation in other countries can provide us a useful benchmark to easily spot the sources of failure and thereby facilitate the development of an effective early banking failure model to enhance liquidity and soundness of the financial system in Ethiopia.

1.3. Objective of the Study

1.3.1. General Objective

The general objective of the paper is to develop a baseline bank failure prediction model for Ethiopian banking industry.

1.3.2. Specific Objectives

- To examine the effects of bank specific variables (capital adequacy, assets quality, management ability, earning and liquidity) in predicting bank failure.

- To develop a baseline bank failure prediction model derived from the influential variables identified above.

1.4. Hypothesis of the Study:

In order to answer the research question the following hypotheses have been proposed for the study:

a) **H_1:** capital adequacy has statistically significant in predicting bank failure.
   H_0: capital adequacy has statistically insignificant in predicting bank failure.
b) **H_1:** asset quality has statistically significant in predicting bank failure.
   H_0: asset quality has statistically insignificant in predicting bank failure.
c) **H_1:** management efficiency has statistically significant in predicting bank failure.
   H_0: management efficiency has statistically insignificant in predicting bank failure.
d) **H_1:** earning ability has statistically significant in predicting bank failure.
   H_0: earning ability has statistically insignificant in predicting bank failure.
e) **H_1:** liquidity has statistically significant in predicting bank failure.
   H_0: liquidity has statistically insignificant in predicting bank failure.

1.5. Significance & Expected Outcomes of the Study

Bank failure could exert terrible consequences on the banking system and an extensive repercussion on the whole economy at large (Adeyeye et al, 2015). To this effect, the relevance of developing a baseline bank failure prediction model for the Ethiopian banking industry are within following points.

First, the development of this model will serve as a tool in helping NBE in identify red flagged banks early before actual failure happens there by limiting the scope and cost of bank failures. This will enhance the soundness of the financial system in Ethiopia.

Second, the result of findings will be of immense benefit to all banks in Ethiopia since it will help them identify the sources of failure; particularly the significant variables to look out for.

Above all, this research will pave the way for other researchers to get familiar with problems in other countries that didn't actually happened in our case, but can happen at any given time. When the real problem happens on the ground, researchers can take timely remedial policy or preemptive action to avoid, if not minimize, the impact of the problem.

1.6. Scope and Limitation of the of the Study

A few points about the scope and limitation of this study are in order.

- The scope of the study is developing bank failure prediction model for the Ethiopian banking industry using bank specific data with the contribution of binary logistic regression model.
- In the absence of any bank failure experience in our country, the researcher used other countries' failed banks data.
- Due to scarcity of publicly available data on failed banks especially from developing countries, the choice of approach was reduced to the two countries, namely Turkey and US. These countries were selected because of the availability and accessibility of their information regarding failed bank.
- Despite difference observed in the real causes of bank failure across the globe, it is empirically proven that banks do exhibit similar characteristic when they are on the verge of failure, like running out of liquidity, deteriorating in asset quality and decline in earning. Against this hard fact, failed banks' empirical experience from Turkish and U.S. are presupposed to proxy bank failure problem in other countries.
- This research didn't account for county specific differences and macroeconomic environment, only bank specific variables are considered.

1.7. Operational Definition of Bank Failure

Before turning to our focus to developing a bank failure prediction model, it is perhaps useful to first establish a working definition for what bank failure is. Bank failure is defined as a situation where at least one of the following events has taken place. The first is the situation where the bank files a bankruptcy. The second situation is where a bank find itself fall in to the hands of other strong bank via merger or acquisition due to financial distress. The other situation for bank failure is when the central bank or any federal depository insurance company (like FDIC for US & SDIF for Turkish) officially bails out or undertake a federal takeover of a troubled bank.

1.8. Organization of the Study

Part one introduced the reader to the background of the problem, specification of the problem, the purpose of the study along with the scope and limitation. The second part of this paper will provide an overview of previous empirical literatures' contribution in the field of bank failure prediction models alone with the description of method used. Part three of this research describes the methodology along with the data set, variables used and econometric model used. Part four discusses the econometrics results. The last section of this study provides the conclusions and recommendation based on the empirical findings.

Chapter II

2. Empirical Review of Literatures

2.1. Introduction

Following the Great Depression of 1930, there was a practical need for bankruptcy prediction models (Saastamoinen et al, 2015). It's, however, during the 1960's that researchers begun to use advanced statistical models to identify financial ratios that could classify companies into failure or non-failure groups (Tuvadaratragool et al 2013). Numerous researches have been conducted to identify early warning indicators of financial distress or failure occurred in different companies using different techniques. The techniques that have been applied to solve bankruptcy prediction problem in banks and firms are broadly divided to two categories: statistical and intelligence techniques. The set of statistical prediction methods include linear discriminant analysis (LDA), multivariate discriminate analysis (MDA), quadratic discriminant analysis (QDA), multiple regression, Logistic Regression (Logit), Probit and factor analysis (FA) (SirElkhatim et al, 2013). The most well know and practical artificial intelligence techniques are neutral networks (NNs), case-based reasoning, decision tree, operational research, rough sets, and soft computing techniques. The review of empirical studies will lay emphasis on the type of technique used, the number of companies involved in the respective research and the overall predictive accuracy of the particular model. Since the researcher opted to address his paper using Logit Model, focus will be given to this model.

2.2. Foundation for Failure Prediction Models

In his pioneered experimental design, Beaver (1966), using a univariate or linear discriminant analysis, assessed the relationships between a single financial ratio of firms as predictive variable and the resultant firm failure. He used 79 failed companies and a matched sample for 79 healthy firms during the years 1954 to 1964 from 38 industries. Beaver investigated the 30 financial ratios that he used in predicting the firms' bankruptcy that leads to failure and found out that six financial ratios could discriminate well between failed and non-failed firms. The financial ratios are grouped in to best predictor, second best predictor and worst predictor. The best discriminant factor was the cash flow to debt ratio, which correctly identified 90 percent of the firms one year prior to failure. The second best discriminant factor was the net income to total assets ratio, which had 88 percent accuracy. Beaver, in his concluding remarks, suggested those financial ratios are useful for bankruptcy prediction. Despite there have been relatively few studies using the simple univariate discriminant model for failure prediction, and researchers tremendously applied multivariate models instead as it accounts more than one variable to explain/predict the failure/non-failure scenario, the work of Beaver gave a solid base for future research in this field.

Altman (1968), who expanded the univariate approach to a multivariate, was the first researcher to introduce the so called Z-Score using multivariate discriminant analysis (MDA) approach to distinguish failure from non-failure firms. The multivariate model allows one to assess the relationship between failure/non-failure and a number of predictive variables. In his study a group of 66 American manufacturing companies, 33 healthy and 33 bankrupt, listed on the Stock Exchange were used. Initially, Altman identified 22 financial ratios in his original data sets and from which he constructed the Z-score model that consisted of 5 ratios. Variables were classified under five different categories: liquidity, profitability, leverage, solvency and activity. The five financial ratios used in his model were working capital/total assets, retained earnings/ total assets, earnings before interest and tax/total assets, market value of equity/book value of total liabilities, and sales/total assets. The model was extremely accurate since the percentage of correct predictions was about 95% for data one year prior to bankruptcy; correctly differentiated 94% of failed companies and 97% of the non-failed companies with data one year prior from failure. However, the model's predictive capability decreases drastically with two and three years before the actual bankruptcy occurred. For example, the model incorrectly predicted 28% of failed firms in to none failed ones when predicting two years prior to the actual failure, and this will discouragingly rose to 52% and 71% when predicting three and four years prior to failure, respectively. Until the end of the 1970s, discriminant analysis remained the dominant method in the prediction of failure. Following his footstep, Deakin (1972), Stuhr et al (1974) and Sinkey (1975) undertake studies assessing the predictability of bank failures using MDA. In his later study, in 1977 and 1994, Altman himself used the MDA while predicting failure.

Until the end of 1980s MDA was the dominant for bankruptcy prediction. However, the restrictive assumptions of the discriminant analysis, for example the assumptions that require the linear relationship between dependent and independent variables and the requirement for the financial ratios to be normally distributed, questioned the real applicability of the model (Karels et al, 1987 & Van der Ploeg et al, 2010). As a result, it was the seminal work of Martin (1977) that introduced the first method of failure prediction that did not make any restrictive assumptions regarding the distributional properties of the predictive variables. The Logistic regression, often referred to as the Logit Model or the Logit Analysis, take into account the probability that the firm will go bankrupt, has been the most employed statistical method for the purpose of failure prediction to date. In the examination of the performance of the Logit model, Martin examined all commercial banks that were member of the Federal Reserve as of 1974. This group of banks contained 23 failed banks and 5,575 non-failed banks. The set of predictive variables comprised 25 ratios of financial statement data that could be classified into four groups, being asset quality, liquidity, capital adequacy, and earnings. Through step-wise procedures, only four among the 25 predictive variables were found to be significant predictors, representing asset quality, capital adequacy and earnings. The ratios are Gross Capital / Adjusted Risk Assets, Charge-Offs / (Net Operating Income + Loss Provision), Commercial and Industrial Loans + Loans to REITs and Mortgage Bankers + Construction Loans + Commercial Real Estate Loans and Commercial and Industrial Loans + Loans to REITs and Mortgage Bankers + Construction Loans + Commercial Real Estate Loans.

Following Martin, in 1980 Ohlson used the Logit model to increase the accuracy of the model in prediction business failure to more than 95%. He used a sample of 105 bankrupt firms and 2,058 non-bankrupt firms for the period 1970-1976. The nine financial ratios included in the model were the logarithms of the company assets, total liabilities/total assets, working capital/total assets, current liabilities/current assets, a dummy variable indicating whether total assets were greater or less than total liabilities, net income/total assets, funds from operation/total liabilities, dummy variable indicating whether net income was negative for the last two years and change of net income. The classification accuracy reported by him was 96.12%, 95.55% and 92.84% for prediction within one year, two years and three years prior to the actual failure, respectively. Four out of the nine financial variables were found to be statistically significant in bankruptcy prediction. These variables were: 1. size of the company, 2. leverage of the company measured as total liabilities divided by total assets, 3. financial performance of the company measured as net income divided by total assets and/or funds provided by operations divided by total liabilities, and 4. company’s liquidity measured by working capital divided by total assets. The model was able to classify 96.12% of the companies correctly, with a cut-off point of p=0.5 (Ohlson 1980).

In 2001 Shumway (2001), proposed a time discrete Hazard model for bankruptcy prediction, which utilized both financial statement and market information. The difference between a hazard model and original logistic model is that in the hazard model the whole time span of a company’s history can be included in the model at once, whereas in the logistic model one financial statement is seen as one observation. Otherwise, these models are somewhat similar since the hazard model uses a logistic regression function. When comparing the prediction power and information content of hazard models to other bankruptcy prediction models, they have been found out to be superior. Apart from slight prediction accuracy difference the results from the Logit model are, in general, consistent and accurate as that of the Hazard Model.

While hazard models are also counted as statistic models, another set of prediction tools is utilized to bankruptcy prediction as well. These so called artificial intelligence expert systems (AIES) include modern concepts like neural networks and genetic algorithms. These systems rely on the modeling of human intelligence and reasoning. The average overall accuracy of neural networks and genetic algorithm models is found to be 87%, which is exactly the same than with logistic models (Aziz et al, 2004).

In addition to these three aforementioned new techniques, lots of other models are discussed in the current literature of bankruptcy prediction as well. But none of these models came up with a significant degree of improving the prediction accuracy than just adding complexity to understand how results are formed. This might be one of the reasons why MDA and logistic regression are probably still the most used models when analyzing probability of bankruptcy. Accordingly, the researcher will give focus on this research outputs.

2.3. Review of other works made in Predicting Failure/Bankruptcy

Avery & Hanweck, using the Logit Model (1984), examined 100 failed banks and 1,190 non-failed banks during an estimation period from December 1978 and to June 1983. The examination of these banks was performed employing an initial set of only nine predictive variables that were selected as they proved to be significant in previous studies. Five of these predictive variables proved to again be significant and displayed the correct a priori expected signs. Consistent with the findings of Martin, the significant variables could be classified into capital adequacy (Equity Capital + Loan Loss Reserve Allowances) / Total Assets), asset quality (Net Loans / Total Assets, Commercial & Industrial Loans / Net Loans & Natural Logarithms of Total Assets) and earnings (Net Income / Total Assets).

Barth et al. (1985), in their study on failures of thrift institutions between December 1981 and June 1984, again confirm the relevance of asset quality, capital adequacy and earnings. In addition to these three risk factors, Barth et al. (1985), employing the Logit Model, find liquidity to be an important factor in relation to subsequent failures. The initial set of predictive variables of the study of Barth et al. only comprised 12 ratios of financial statement data that, consistent with Avery & Hanweck (1984), were selected as they proved to be significant in previous studies. From 12 ratios used the Net Worth / Total Assets, Interest Sensitive Funds / Total Funds, Net Income / Total Assets, Liquid Assets / Total Assets & Natural Logarithm of Total Assets being an important significant variables in predicting failure.

West (1985) uses the Logit model, along with factor analysis, to measure and describe banks' financial and operating characteristics. Data was taken from Call and Income Reports, as well as Examination Reports for 1,900 commercial banks in US. According to the analysis, the factors identified by the Logit model as important descriptive variables for the banks' operations are similar to those used for CAMELS ratings. He demonstrates that his combined method of factor analysis and Logit estimation is useful when evaluating banks' operating conditions.

Pantalone and Platt (1987) apply Logit regression Analysis to study the explanatory variables which discriminate between bankrupted and non-bankrupted banks in the US. The sample they used consists of 113 bankrupted and 226 non-bankrupted banks for the period 1983-84. The empirical findings demonstrate that the main reasons of bankruptcy are inefficient credit risk management, excess risk, inefficient control and monitoring. The model accurately predicted failed and non-failed banks with 86.7% and 83.4% level of accuracy, respectively.

Lau (1987) using Logit analysis had better predictability for three years. The three years are 96%, 92%, and 90%, respectively.

Aziz and Lawson (1989) utilized cash flow information based on the operating cash flow model of Lawson to predict financial distress. The authors used the Z-score model, Zeta score model, Logit analysis model and a mixed model to predict financial distress on 49 matched companies between 1973 and 1982. The overall comparative classification and predicative accuracy on the hold-out sample between the Z-score model, Zeta score model, Logit analysis and mixed model were 77.4%, 92.8%, 76.3% and 82.8% respectively. The authors argued that operating cash flows were important variables to predict financial distress.

Thomson (1991) examined the banking failure that took place in the United States FDIC-insured commercial banks during the 1980s. He examines the predictive accuracy of the Logit Model employing predictive variables that proxy for asset quality, capital adequacy, earnings, liquidity and management quality. Argumentation behind the inclusion of the risk factor management quality was based on an earlier study of Graham & Horner (1988) that illustrated the importance of an adequate management. The results of Thomson, based on failures between 1984 and 1989, demonstrated that the probability of bank failure is a function of the following variables (Book Equity + Loan Loss Reserves – Loans 90 Days Past Due - Non-Accruing Loans) / Total Assets, Net Charge-Offs / Total Assets, Overhead / Total Assets, Return On Assets and (Federal Funds Purchased – Federal Funds Sold) / Total Assets. The Logit Model, including variables of all five risk factors, demonstrated very good classification accuracies both in-sample as well as out-of-sample.

Bell (1997) compares Logit and BPNN models in predicting bank failures. In his study, he uses 28 candidates for predictor variables. He finds that neither the Logit nor the BPNN model dominates the other in terms of predictive ability. However, BPNN is found to be better for complex decision processes.

Iyoha and Udegbunam (1999) used Logit regression analysis to predict bank failure in Nigeria. The result indicate overall correct predictions ranging from 62 per cent in 1991 to 88 per cent in 1993, an indication that the model's predictive power increases over time. That is, as the date of failure draws closer, the model's predictive power equally increases.

Estrella et al. (2000), employing a Logit model, examine and compare the effectiveness of simple and more complex risk-weighted capital ratios, representing the risk factor capital adequacy. They conclude that simple capital ratios predict bank failures as well as the more complex risk-weighted capital ratios and that therefore the risk factor capital adequacy can without problems be proxied by a number of simple capital ratios. Estrella et al also examine the performance of credit ratings as a predictor of default. However, evidence in favor of credit ratings being important predictors of defaults is somewhat mixed.

Kolari et al (2002) developed an early warning signal (EWS) based on Logit and the Trait Recognition (TR) methods for US banks. The Logit model correctly classifies over 96% of the banks one year prior to failure and 95% of the banks two years prior to failure. They find that with data classification both one year and two years prior to failure, the accuracy of the Trait Recognition model is 100%. Therefore, they conclude that the Trait Recognition model outperforms the Logit Model in terms of type-I and type-II errors.

Becchetti and Sierra (2003) apply a Logit model using non-financial variables to identify bankruptcy determinants in three representative unbalanced samples of Italian firms for the periods 1989–91, 1992–94 and 1995–97. The authors conclude that qualitative variables such as customers' concentration are significant explanatory powers.

Canbas et al (2005) propose an Integrated Early Warning System (IEWS) that combines DA, Logit, Probit, and Principal Component Analysis (PCA), which can help predict bank failure. By combining all these together, they construct an IEWS. The authors use the data for 40 privately owned Turkish commercial banks to test the predictive power of the IEWS, concluding that the IEWS has more predictive ability than the other models used in the literature.

Nurazi and Evans (2005) investigated whether CAMELS ratios can be used to predict bank failure in Indonesia. The results found that Logistic Regression in tandem with multiple discriminant analysis could function as an early warning system for identifying bank failure and as a complement to on-site examination. From the 13 variables used representing CAMELS ratios including bank size, the results suggest that the variables Equity Capital/Total Assets (adequacy ratio), Earning Before Income Tax/ Productive Assets (assets quality), Net Income/Total Assets (management), Operating Expenses/Operating Income (earnings), Cash and Bank/Total Deposit (liquidity), and Natural Logarithm (Ln) of Bank Assets Size (bank size) are statistically significant in explaining bank failure. And the ability of the model in predicting bank outcome (failure/non failure) is remarkable, as it predicted 90.2% accurately.

Montgomery et al (2005) investigated empirically the cause of bank failure in Japan and Indonesia. Using Logistic regression analysis of financial ratios, the researchers explore the usefulness of domestic bank failure prediction models with a cross-country model that allows for cross-correlation of the error terms. Seventeen financial ratios were selected as predictor variables that proxy for the fundamental condition and performance of the banks' under study (failure and non-failure). The entire population of commercial banks in Indonesia and Japan were taken. In Indonesia, the data were taken for fiscal years 1997-2003, while for Japan the period extends from 1978 to 2001. From the data, three different models were developed; Japan, Indonesia and the Cross-country Model. Goodness of fit test for all three bank failure prediction models display good fit with actual observed bankruptcy. With stepwise Logistic Regression that uses factor analysis to reduce the number of independent variables used in the regression by identifying those variables which are most informative in predicting bankruptcy shows the following results. For both domestic prediction models, the behavior of loans, in particular the ratio of loans to deposits or loans to equity, are significant indicators of bankruptcy. In Indonesia the ratio of loans to total assets and nonperforming loans are also significant indicators of bankruptcy. The result was not surprising for the researchers, as troubled banks may increase lending in the face of financial difficulty as a way of bringing in revenue and this lending may in fact tend to go to riskier borrowers who can pay higher interest rates. For the domestic Japanese model, the fact that OTA (ratio of other securities to assets) and ROA (return on assets) enter positively is contrary to the expectations of the researcher. In the case of ROA, this may be signaling increasing risk, requiring higher return on assets. The cross-country stepwise regression results also suggest that loan behavior is very significant in predicting bankruptcy. The loan to equity ratio and ratio of non-performing loans for Indonesian banks enter statistically significantly in the cross-country model. The ratio of securities to total assets (STA) and for Indonesian banks and equity to total assets (ETA) for both Indonesian and Japanese banks also entered significantly positive, and the odds ratio for STA is particularly large. The predictive powers of all three models are classified over 90% of the outcomes.

Lanine and Vander Vennet (2006) employ a Logit model and a Trait Recognition approach to predict failures among Russian commercial banks. The authors test the predictive power of the two models based on their prediction accuracy using holdout samples. Although both models perform better than the benchmark, the Trait Recognition approach outperforms Logit in both the original and the holdout samples. For the predictable variables, they find that expected liquidity plays an important role in bank failure prediction, as well as asset quality and capital adequacy.

Chi and Tang (2006) used the Logit model to analyze a sample of 240 publicly traded firms including 60 bankrupted firms listed in seven Asia-Pacific capital markets during 2001-2003. Every bankrupted firm is matched with three non-bankrupted ones with regard to 20 independent explanatory variables classified in three categories: financial ratios, firm-specific characteristics and country risk. The empirical results that were obtained from this study show that the Logit method gives satisfying prediction accuracy.

In order to evaluate different models' prediction accuracy, Kim and Gu (2006), use 12 financial rations and both discriminant analysis and Logit methods for a sample of 18 bankrupted and 18 active restaurants in the US for the period 1986-1988. The empirical results show that the Logit method provides better results with an accuracy rate of 94%, while the multivariate discriminant analysis (MDA) generates an accuracy rate of 92%.

Lanine et al (2006) employ a Logit Model and a Trait Recognition approach to predict failures among Russian commercial banks. The authors test the predictive power of the two models based on their prediction accuracy using holdout samples. Although both models perform better than the benchmark, the Trait Recognition approach outperforms Logit in both the original and the holdout samples. For the predictable variables, they find that expected liquidity plays an important role in bank failure prediction, as well as asset quality and capital adequacy.

By using five selected ratios from CAMEL and applying them in to Logistic Regression model, Ronapat et al (2006) developed a bank failure prediction model for the period 2001, 2002 and 2003 using banks listed in the Thailand Stock Exchange. The model result shows that level of accuracy was 66.7%, 42.9% and 100% for one, two and three years prior to failure. Though previous studies suggest that the level of accurately predicting bank failure declines as the number of years prior to the actual bankruptcy gets older, the result only support the first two years (i.e. 2001 and 2002). However, the researcher argues that this counterintuitive happened for the year 2003 was due to strong economy recovery witnessed following the 1997-1998 crisis which resulted in lower number of listed firms going bankrupt, thus, lowering the level of predictability.

Davis and Karim (2008a) evaluate statistical and intelligence techniques in their analysis of the banking crises. Specifically, they compare the Logistic Regression (Logit) and the Signal Extraction EWS methods. They find that the choice of estimation models makes a difference in terms of indicator performance and crisis prediction. Specifically, Logit Model performs better as a global EWS and Signal Extraction is preferable as a country-specific EWS.

Davis and Karim (2008b) test whether EWS based on the Logit and binomial tree approaches could have helped predicting the recent subprime crisis in the US and UK. Using twelve macroeconomic, financial and institutional variables, they find that among global EWS for the US and UK, the Logit performs the best.

Arena (2008) employs both the Hazard Model as well as the Logit Model in order to examine and compare bank failures in East Asia and Latin America. Arena concluded that bank failures can be explained by the individual financial statement data and that systemic shocks, that are different for the two regions and not for banks within a region, primarily destabilized the already inadequate banks in East Asia. The latter conclusion signifies a regional asymmetry regarding the resilience of the banking sector to systemic shocks and hence illustrates the heterogeneity among the banking sectors of different regions. With respect to the individual financial conditions of the banks, represented in the financial statement data, Arena concluded various financial ratios that proxied for capital adequacy, asset quality, and liquidity to be most informative about future bank failures.

A study by Andersen (2008) applying Logit Model determined the most relevant predictors of defaults of Norwegian banks. Out of an initial set of 23 predictive variables, Andersen found six predictors to be most relevant. These six predictors could, consistent with numerous previous studies, be categorized into the general risk factors capital adequacy, asset quality, earnings, and liquidity.

With the aim applying and evaluating four different neural networks (NNs) model, support vector machines (SVM) and three multivariate statistical methods to the problem of predicting bank failures, Boyacioglu et al (2009) took 21 failed and 44 non-failed banks from Turkey from 1997-2003. A total of 20 financial ratios with six featured groups including capital adequacy, asset quality, management quality, earning, liquidity and sensitivity to market risks (CAMELS) are selected as classifiers in the study. The entire data set then classified in to training and validation subsets. Using independent sample t-test only 9 out of 20 variables were able to show significance in making difference between failed and non-failed banks. This ratios are shareholder's equity/total assets, shareholder's equity/total loans, shareholder's equity + net profit/total assets + off balance sheet commitments, total loans/total assets, net profit/average assets, net profit/average shareholder's equity, total loans/total deposits, Trading securities/total assets and net interest income/average assets. As many studies in a number of fields reported, the superiority of multi-layer perceptron (MLP), under neutral network models, in prediction problems is proven in this research too. Based on the experimental results, the model correctly classified 100% of the banks in the training data set, and 95.5% of the banks in the validation set. Likewise, support vector machines (SVMs) correctly classified the 95.34% of banks in the training set and 90.90% of banks in the validation set. On the other hand, despite Logit model placed at the third spot in correctly predicting 86.04% of failure status of the banks in the training set and 81.81% of the banks in the validation set, the level of accuracy can be considered satisfactory.

Ahmadi et al (2012) attempted to predict the bankruptcy of companies using the Logit model. Therefore, they selected a sample of 49 bankrupt companies and 49 non-bankrupt companies for the years 2005 to 2007. In order to designing a model they used 19 finance ratios. Based on research results, Logit model with variables of net profit to total assets ratio, the ratio of retained earnings to total assets and debt ratio have more power to predict corporate bankruptcy in Iran.

With the aim of using the Logit method in predicting the probability of banking defect, Zaghdoudi et al (2013) gathered annual data of the 14 Tunisian banks spanning 8 years, from 2002 to 2010. Eighteen ratios associated to different dimensions of financial analysis that represent the different indicators of banking vulnerability measure were identified. These ratios are regrouped into five groups, liquidity, management, activity, profitability and vulnerability. The most pertinent ratios in the explanation of banking defect at the Tunisian banks were seven amongst the eighteen; Debt / Total Assets, Load Banking / Total Assets, Load Bank / Banking Product, Net banking / Number of employees, Total Credit / Equity, Net banking income / Total Assets and Borrowing / (Capital + Reserve).

Adeyeye et al (2015) developed an integrated early warning signal with three standard statistical models including DA, Logit and Probit models to distinguish failed from non-failed Nigerian banks. The sample for the study covers 23 year period from 1993 to 2010 and comprises of ratios of 21 banks. Eleven financial ratios for both the banks that are known to have failed and surviving ones were computed using data collected from annual financial reports of individual banks. From their estimated results, four explanatory variables were found in Logit model to be significant statistically. They are: capital/total risk-weighted assets ratio, capital/assets ratio, earnings per share, net-income/total assets ratio and total loan/total assets ratio. The results exhibit consistency with outcomes of earlier studies that also used large number of financial ratios (Iyoha and Udegbunam, 1999; Canbas et al., 2005). From the summary results of the three models, it is observed that overall classification accuracy is relatively high in each case with discriminant model recording 95.2% correct classification, probit model recording 89.02% correct classification and Logit model recording 90.24% correct classification respectively. In their concluding remarks, adopting the integrated early warning signal (IEWS), constructed from the three models, could be employed as a support tool for analytical decision for both on-site and off-site bank examinations to distinguish banks which are undergoing severe financial difficulties responsibility to prevent or forestall failure of banks.

From the above literature we can deduce that bank financial performance data does exhibit a predictive power in assessing potential failure of commercial banks. Thus it seems plausible that a model of bank failure incorporating ratios can be developed. Even though there are more modern statistical methods available, such as hazard models and neural networks, Logit method is chosen because of their well-established status in academic research and overall understandability. Therefore it is crucial that banks can understands how the information is generated. Understandability creates trustability, which is strength of this method, whereas hazard models and neural networks are such complex systems that understanding them properly might be challenging.

Table 1: Summary of predictive variables that are found to be Relevant in Relation to Predicting Failure in Previous Studies that fall under CAMEL

S/N	Study	Model Used	Ratio*	Significant Predictive Variables that fall under CAMEL				
				Capital Adequacy	Asset Quality	Management Efficiency	Earning Ability	Liquidity
1	Martin (1977)	*Logit*	*25/4*	*GCARA*	*GCONI* *CI2LN*		*NITA*	
2	Ohlson (1988)	*Logit*	*9/4*		*LNTA*	*TLTA*	*NITA*	*WCTA*
3	Avery & Hanweck (1984)	*Logit*	*9/5*	*KTA*	*NLTA* *CILNL* *LNTA*		*NITA*	
4	Barth et al. (1985)	*Logit*	*12/5*	*NWTA*	*ISFT* *LNTA*		*NITA*	*LATA*
5	Thomson (1991)	*Logit*	*16/7*	*NCAPTA*	*NCOTA* *NLTA*	*OVRHDTA*	*ROA*	*LIQ*
6	Nurazi (2005)	*Logit*	*13/6*	*KTA*	*EBETPA* *LNTA*	*NITA*	*OEOI*	*CBTD*
7	Andersen (2008)	*Logit*	*27/6*	*CAR*	*RMGL* *ELOSS* *CONS*		*ROA*	*NBLI*
8	Boyacioglu (2009)	*Logit* *NNs* *SVM*	*20/9*	*KTA* *KTL* *E+NP/TA+OBS*	*TLTA* *TLTD* *TSTA*		*ROA* *ROE* *NITA*	
9	Adeyeye (2015)	*Logit*	*11/4*	*CAR* *KTA*	*TLTA*		*EPS* *ROA*	

*The ratio of selected predictive variables to significant predictive variables.

Source: the Researcher's Own Compilation

GCARA = Gross Capital / Adjusted Risk Assets, GCONI = Charge-Offs / (Net Operating Income + Loss Provision), CI2LN = (Commercial and Industrial Loans + Loans to REITs and Mortgage Bankers + Construction Loans + Commercial Real Estate Loans) / Total Assets, NITA = Net Income / Total Assets, KTA = (Equity Capital + Loan Loss Reserve Allowances) / Total Assets, LNTA = Natural Logarithm of Total Assets, NLTA = Net Loans / Total Assets, CILNNL = Commercial and Industrial Loans / Net Loans, NWTA = Net Worth / Total Assets, ISFTF = Interest Sensitive Funds / Total Funds, LATA = Liquid Assets / Total Assets, NCAPTA = (Book Equity + Loan Loss Reserves – Loans 90 Days Past Due - Non-Accruing Loans) / Total Assets, NCOTA = Net Charge-Offs / Total Assets, OVRHDTA = Overhead / Total Assets, INSLNTA = Loans to Insiders / Total Assets, ROA = Return On Assets, LIQ = (Federal Funds Purchased – Federal Funds Sold) / Total Assets, CAR = Capital Adequacy Ratio, RMGL = Residential Mortgages / Gross Lending, ELOSS = Expected Loss based on PD / Gross Lending, CONS = Herfindahl Index for Loan Portfolio, NBLI = Norges Bank's Liquidity Indicator, OEOI = Operating Expense / Operating Income, TLTD = Total Loans / Total Deposits, CDR = Total Domestic Time Deposits / Total Assets, NPCR = (Primary Capital – Nonperforming Loans) / Average Total Assets, TLTA = Total Loans / Total Assets, OHR = Operating Expenses / Average Total Assets, TETA = Total Equity / Total Assets, OROTA = Other Real Estate Owned / Total Assets, NPLTA = Nonperforming Loans / Total Assets, CSTIN = Cost Inefficiency, TETL = Total Equity / Total Liabilities, LATL = Liquid Assets / Total Liabilities.

Chapter III

3. Research Design

The methodology used and the specification to construct the Logit model will be described in the first section. Following that, source and type of data used will be presented. Finally, the different variables used along with their description and relation with the probability of failure will be presented.

3.1. Research Methodology

As we have seen in the literature review part, until the end of the 1970s, discriminant analysis remained the dominant method in the prediction of failure. In spite of this, restrictive assumptions of discriminant analysis, e.g. discriminant analysis assumes the financial statement data to be normally distributed and assumes the variance-covariance matrices of failed and non-failed banks to be equal, were proven to be violated frequently by multiple subsequent studies (Ko et al, 2001). Since the seminal work of Martin (1977), the logistic regression, often referred to as the Logit model or the Logit analysis, has become one of the most commonly applied parametric failure prediction models in both the academic literature as well as in the banking regulation and supervision as it fills the gaps of the discriminant analysis (Van der Ploeg et al, 2010). Logit analysis is the most commonly employed early warning signal methodology applied in business academic studies as well as bank regulatory practice, especially in detecting potential failure risk (Jagtiani et al, 2010).

The Logit Model has the statistical property of not assuming multivariate normality among the independent variables, contrary to the probit model that does assume a normal distribution of the data. This can be seen as an advantage when analyzing banking data; which is generally is not normally distributed. Logistic regression applies maximum likelihood estimation to calculate the logit coefficients after transforming the dependent into a logit variable (the natural log of the odds of the dependent occurring) (Hosmer and Lemeshow, 1989). In this way, logistic regression estimates the probability of a certain event occurring.

Despite the widespread popularity of Logit analysis as an effective early warning system, it does have some drawbacks. The first problem encountered in the model is that it is not possible to determine which variables are most useful in predicting failed banks versus non-failed banks. The results only indicate the effectiveness of each variable in discriminating between failed and non-failed banks. The model doesn't also provide any information about how each variable affects Type I (misclassifying failed banks as non-failed) and Type II errors (non-failed banks misclassified as having failed).

To evaluate the impact of CAMEL (capital adequacy, asset quality, management ability, earning and liquidity) on the probability of bank failure, the researcher employed Logit Model. The objective of using a logistic regression model is to determine the financial ratios as explanatory variables in the model that are significantly related to the response variable in the model which is probability of banks failure and non failure. The researcher subjected the model to robustness by testing and examining its performance with respect to the actual prediction power from the sample banks. In addition, after the model is built, the statistical significance of each of the coefficients can be evaluated using the Wald test. The Wald statistic is commonly used to test the significance of individual logistic regression coefficients for each independent variable (Bewick et al, 2005).

The specification of the logistic regression model is:

$$\text{Log}\,[P_{Li}/(1-P_{Li})] = \alpha + \sum_{n=1}^{n} = \beta_n X_{ni}, \text{ or}$$

$$\text{Log}\,[P_{Li}/(1-P_{Li})] = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

P_{Li} – the probability of banks i's failure.

α = Intercept

β_1 ….., β_n - are regression coefficients indicating the relative effect of a specific predictor on the outcome.

X_1,…., X_n are the are the explanatory variable.

From the logistic regression model, the estimated value of the dependent variable can be interpreted as the predicted probability of bank failure (PLi). By solving the PLi through Eq. (1), the predicted bank failure probability is described as

$$P_{Li} = \frac{e^y}{(1+e^y)}$$

Where:

e- is the base of natural logarithm

y- equals $\alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni}$

Logistic regression model generates coefficient estimates for each of the financial ratios and associated test statistics that indicate how well it identify between failed and non-failed banks. Based on that probability a bank is classified as failed or non-failed, using a cut-off probability, attempting to minimize the type I (failed banks classified as non-failed banks) and type II (non-failed banks classified as failed banks) errors (Mcleod et al, 2004).

To classify sample banks into a failed group or a non-failed group, the Logit value of each sample bank is calculated based on the estimated model and then it was applied to the probability function,

$$PLi = \frac{e^y}{(1+ e^y)}$$

In this study, banks with P_{Li} values less than or equal to 0.5 are classified into the non-failed banks and banks with P_{Li} values more than 0.5 are classified into the failed.

3.2. Data Collection and Sampling

In this study the researcher used bank specific data on Ethiopian, U.S. and Turkish banks which are drawn from financial statements of the respective banks. The data are taken on the annual basis from 2008/09 to 2013/14 for Ethiopian banks and from 1997 to 2000 for Turkey banks and from 2008 to 2014 for U.S. banks. These periods were chosen for Turkish and US banks because it was during this time that the Turkish and U.S. faces financial crisis leaving abundant failed banks. The researcher tried to predict financial failure in these banks one year ahead of financial failure date. For this reason, failed banks' balance sheets and income statements from the period one year prior to the financial failure are used. The researcher only uses the year-end financial statements in the analyses. The researcher used 19 financial ratios that are calculated from the financial statements of the respective banks as explanatory variables. All variables are bank specific. The researcher does not include any macro variable because of substantial differences with respect to economic situation across these countries. These ratios are selected to represent capital adequacy, asset quality, management ability, earning ability and liquidity (or simply, CAMEL).

All of the 18 commercial banks operating in Ethiopia were included in the study, but some of the banks historical data are not available since they were not operational at that given periods. From 2008/09 to 2013/14 financial period the total number of observations come up to 92.

Table 2. Sample Size for Ethiopian Banks

Period	Number of Banks		
	Failed Banks (One Year Prior to Failure)	Non-failed Banks	Total Banks
2008/09	0	12	12
2009/10	0	14	14
2010/11	0	15	15
2011/12	0	16	16
2012/13	0	17	17
20/1314	0	18	18
Grand Total	**0**	**92**	**92**

Source: the Researcher's Own Compilation

The data base for developing baseline bank failure prediction model consists of US banks. In order to have sufficient sample size of failed banks in my data base, I extracted 93 failed banks, from 2008 through 2014. Since the model requires non-failed banks in the data set, equivalent number of non-failed banks is also extracted (i.e. 93). This will help the model to have sufficient sample size that is capable of producing robust logistic regression result[1]. Those banks that are classified as failed banks in US are based on the classification given by FDIC.

Table 3. Sample Size for U.S. Banks

Period	Number of Banks		
	Failed Banks (One Year Prior to Failure)	Non-failed Banks	Total Banks
2008	22	22	44
2009	23	23	46
2010	16	16	32
2011	13	13	26
2012	11	11	22
2013	8	8	16
Grand Total	**93**	**93**	**186**

Source: the Researcher's Own Compilation

For Turkish case, the researcher identified 15 failed banks that have adequate data for the analyses. Likewise, equal number of non-failed banks data is also extracted for Turkish case. Accordingly, equal numbers of non failed banks were selected randomly. Those banks that are classified as failed banks are base of the classification given by Savings Deposit Insurance Fund SDIF of Turkey.

[1] *A larger sample size is needed to insure power of the statistical procedure. It is recommended that a sample size be at least 10 cases per independent variable (Westland et al, 2010)*

Table 4. Sample Size for Turkish Banks

Period	Number of Banks		
	Failed Banks (One Year Prior to Failure)	Non-failed Banks	Total Banks
1997	2	2	4
1998	3	3	6
1999	1	1	2
2000	9	9	18
Grand Total	**15**	**15**	**30**

Source: the Researcher's Own Compilation

The sources of the data are from the web-page of FDIC for US banks and Banker Association of Turkey (BAT) for Turkish banks. National Bank of Ethiopia was the source of the data for the Ethiopian banks.

The sampling method employed in selecting failed and non-failed banks from the U.S was using simple random sampling. But caution was made while selecting individual US and Turkish banks for their asset size not to exceed USD 4 billion. Although Turkish non-failed banks are selected randomly (using simple random sampling), failed banks was screened based on data availability.

Finally, the entire data set is composed of 200 non-failed vs. 108 failed banks, with the total observation of 308. The splits of failed and non-failed banks are summarized in the following table.

Table 5. Summary Table on Total Sample Size

Observation	Number of Observation		
	Failed Banks (One Year Prior to Failure)	Non-failed Banks	Total Banks
Total	108	200	308

Source: the Researcher's Own Compilation

3.3. Description of Predictive Variables

There are, typically, several predictive variables that provide sound and reliable forecast for bank failure prediction model. Researchers start out with either a vast number of predictive variables or select a small set of predictive variables that were found to be significant relevance in previous researches on bank failure. Regardless of the approaches by which the predictive variables are selected, there are no consensuses as to which predictive variables are intended to proxy bank failure more. However, capital adequacy, asset quality, management quality, earnings and liquidity are commonly found significant. Because of the simple structure, the use of CAMEL risk factors has become widespread in empirical literature. Predominantly empirical literature on US bank failures employs financial ratios that are related to the CAMEL risk factors (Arena et al, 2008).

Following the established literature and from the researcher contribution, the study employed 19 variables for predicting bank failure. Categorically, three were from capital adequacy; three from assets quality; two from management quality; eight from earning ability; and three from liquidity.

A) Capital Adequacy

Capital adequacy is a measure of bank financial resilient to unforeseen and abnormal shocks to overcome the risk of insolvency. That is, a bank's equity capital acts as a last resort or defense against failure. For this study, three proxies are used to assess capital adequacy.

For this study, the risk factor capital adequacy is proxied by 3 financial ratios.

C1- *Equity Capital/ Asset*
This ratio is expected to exhibit a negative relationship with the probability of failure.
C2- *Equity Capital/ Net-Loan*
This ratio is expected to exhibit a negative relationship with the probability of failure.
C3- *Equity Capital/ Liability*
This ratio is expected to exhibit a negative relationship with the probability of failure.

Therefore, I hypothesize the following:
Hypothesis 1: Capital Adequacy ratios are expected to have a significant relationship to the probability of failure.

B) Asset Quality

Asset quality is the second crucial element of CAMEL. It measures the quality of the bank's earning assets, including the bank's loan portfolio (credit risk) and securities portfolio (market risks) as well as off-balance-sheet items (e.g., guarantees, letters of credits and derivative instruments) (FDIC website). Poor asset quality is associated bank failure due to large expense allotted in the form of provision and possible written offs. Based on practical and conceptual considerations, this study proxy Asset Quality by three predictive variables.

A1- *Loan Loss Reserve /Net-Loan*
This ratio is expected to exhibit a positive relationship with the probability of bank failure.

A2- *Loan Loss Reserve / Equity Capital*

This ratio is expected to exhibit a positive relationship with the probability of bank failure.

A3- *Loan Loss Provision / Net Interest Income*

This ratio is expected to exhibit a positive relationship with the probability of bank failure.

Therefore, I hypothesize the following:

Hypothesis 2: Asset Quality ratios are expected to have a significant relationship to the probability of failure.

C) Management Quality

The managerial quality of the bank, the third CAMEL covariate, is usually very difficult to measure objectively based on financial statement data. However, following Altman (1968), Halling & Hayden (2006) and Godlewski (2007), among others, this study attempts to approximate for the quality of the management my measuring the ability of managers in generating maximum revenue out of less expenditure. Based on practical and conceptual considerations, this study proxy Management Quality by two predictive variables.

M1- *Operating Expense / Operating Income*

Ratio M1 reflects the ratio of expenses and income. High expenses in combination with relatively low income, i.e. a high ratio of M1, are expected to result in a higher probability of default.

M2- *Gross Yield on Assets*

Is the ratio of total income to assets and serves as a measure of asset management efficiency. A higher ratio reflects higher earning and hence lower probability of failure.

Therefore, I hypothesize the following:

Hypothesis 3: Management Quality ratios are expected to have a significant relationship to the probability of failure.

D) Earning Ability

For this study, nine proxies are used to assess earning ability.

E1- *Return on Asset (ROA)*

A high ratio implies a high efficiency and a high operational performance and is therefore preferred, implying a negative expected relationship with the probability of failure.

E2- *Return on Average Equity (ROE)*

A high ratio implies a high profitability and is therefore expected to exhibit a negative relationship with the probability of default.

E3- *Interest Income/Interest Expense*

A high ratio implies a high profitability and is therefore expected to exhibit a negative relationship with the probability of default.

E4- *Profit Margin*

Profit margin, which is the ratio of net profit before tax to total income, indicates how well management and staff have been able to keep the growth of revenues ahead of rising costs. A high ratio implies a high profitability and is therefore expected to exhibit a negative relationship with the probability of default.

E5- *Net Interest Margin*

The net interest margin measures the net interest income relative to assets. Hence, a higher or positive net interest margin is expected to exhibit a negative relationship with the probability of default.

E6- *Overhead Efficiency Ratio*

Overhead efficiency ratio shows effort to cover non-interest expenses through non-interest income and net-interest income. All factors being equal, the lower the ratio, the lower and the probability of failure.

E7- *Return on Loans*

This ratio measures the profitability of a bank from the perspective of interest income, which is one of the major sources of a bank's income. When the ratio of interest income to loan is high, this signals a high profitability on interest, which is preferable and will decrease the probability of failure.

E8- *Profit before Tax / Interest Expense*

A high ratio signifies a high profitability and is therefore preferred. The relationship with the probability of failure is expected to be negative.

Therefore, I hypothesize the following:

Hypothesis 4: Earning Ability ratios are expected to have a significant relationship to the probability of failure.

E) Liquidity

Liquidity, the last covariate, is measured to determine a bank's exposure to liquidity risk. Banks are highly concerned with liquidity risk; that is, the chance that bank will not be able to meet its current financial obligations (e.g., those of depositors) because of insufficient current assets such as cash and quickly marketable securities, especially during economic recession (Golin, 2001). In this study, the risk factor liquidity is proxied by three predictive variables.

L1- *Cash & Bank Balance / Deposit*

A lower ratio signifies low liquidity and it might trigger higher risk of possible deposit run-off and thus failure.

L2- *Net-Loan / Asset*

This liquidity ratio indicates what percentage of the assets of a bank is tied up in loans. The higher this ratio the less liquid the bank will be. Hence, the relationship with the probability of failure is expected to be positive.

L3- *Net-Loan / Deposit*

This ratio is similar to L3. The relation between this ratio and the probability of default is expected to be positive.

Therefore, I hypothesize the following:

Hypothesis 5: Liquidity ratios are expected to have a significant relationship to the probability of failure.

Table 6: Summary of Selected CAMEL Ratios for Predicting Bank Failure

S/N	Categories	Ratio	Abbreviation	Expected Sign with Failure	Code
1	Capital Adequacy	Equity Capital/ Asset	E/A	-	C1
2		Equity Capital/ Net-Loans	E/L	-	C2
3		Equity Capital/ Liability	E/Li	-	C3
4	Asset Quality	Loan Loss Reserve / Net-Loans	Res./L	+	A1
5		Loan Loss Reserve / Equity	Res./E	+	A2
6		Loan Loss Provision / Net Interest Income	Pro./NII	+	A3
7	Management Quality	Operating Income/ Operating Expense	OX/OI	+	M1
8		Gross Yield on Assets= Total Income/ Total Assets	GYoA	-	M2
9	Earning Ability	Return on Asset	RoA	-	E1
10		Return on Equity	RoE	-	E2
11		Interest Income / Interest Expense	II/IX	-	E3
12		Profit Margin= Profit before Tax/Total Income	PM	-	E4
13		Net-interest Margin= (Interest Income-Interest Expense)/Total Assets	NIM	-	E5
14		Overhead Efficiency Ratio= Non-interest Expense/(Non-interest Income + Net Interest Income)	OER	+	E6
15		Return on Loans= Interest Income/Net-Loans	ROL	-	E7
16		Profit before Tax/Interest Expense	PbT/IX	-	E8
17	Liquidity	Cash and Bank/Deposit	C&B/D	-	L1
18		Net-Loans/Asset	L/A	+	L2
19		Net-Loans/Deposit	L/D	+	L3

Source: Compiled by the Researcher

Chapter IV

4. Data Presentation and Analysis

4.1. Descriptive statistics

Prior to delving into analysis it is relevant to identify if there is any significant differences between the two groups of banks (i.e. failed and non-failed). Initially, this was accomplished through the calculation of the descriptive statistics for all financial ratios used in the study. The following table illustrates the means of the nineteen representative statistical variables one year prior to bank failure. As per the table, the mean of all of the nineteen variables are statically different across the two groups of banks and the sign of most of the observation are consistent with the researcher expectations.

Table 7. Group Statistics

Variables	Status of Bank	Mean	Std. Deviation
C1	Failed Bank	5.548	2.5259
	Non-failed Bank	11.611	5.6018
C2	Failed Bank	9.253	6.6166
	Non-failed Bank	26.486	25.1268
C3	Failed Bank	5.877	2.7986
	Non-failed Bank	13.998	9.6609
A1	Failed Bank	4.313	3.4906
	Non-failed Bank	2.289	2.0627
A2	Failed Bank	65.511	73.5128
	Non-failed Bank	13.197	15.7472
A3	Failed Bank	77.219	154.3797
	Non-failed Bank	13.641	45.4735
M1	Failed Bank	122.245	74.8974
	Non-failed Bank	78.830	295.0142
M2	Failed Bank	8.289	7.9740
	Non-failed Bank	6.798	2.5319
E1	Failed Bank	-3.486	6.4494
	Non-failed Bank	1.309	1.6692
E2	Failed Bank	-88.933	180.8111
	Non-failed Bank	11.748	21.0358
E3	Failed Bank	305.373	200.7489
	Non-failed Bank	419.442	334.5917
E4	Failed Bank	-62.808	75.7166
	Non-failed Bank	23.497	65.3863
E5	Failed Bank	3.463	2.5460
	Non-failed Bank	3.064	.9289
E6	Failed Bank	340.239	1062.9794
	Non-failed Bank	76.413	49.3526
E7	Failed Bank	15.372	24.4576
	Non-failed Bank	9.239	2.8942

Continued…

Variables	Status of Bank	Mean	Std. Deviation
E8	Failed Bank	-202.146	369.3737
	Non-failed Bank	118.962	197.2902
L1	Failed Bank	8.849	7.0973
	Non-failed Bank	29.203	25.6842
L2	Failed Bank	65.512	14.7344
	Non-failed Bank	52.194	16.7154
L3	Failed Bank	76.730	20.7089
	Non-failed Bank	66.959	19.6848

Number of Observation- Failed-108, Non-failed-200
Degree of Confidence interval is 95%

Since all of the variables identified above are drawn from the same balance sheet, income statement or both, problem of multicollinarity should be checked prior to running the binary logistic regression. Although multicollinearity doesn't affect the overall goodness-of-fit of the model, it does, however, make the model more difficult to determine the individual role of each the predictor in explaining the outcome (Pindyck, Rubinfeld, 1997).

Hamilton (2006, p.210) describes the problem of multicollinarity as, "When we add a new x variable that is strongly related to x variables already in the model, symptoms of possible trouble include the following:

a) Substantially higher standard errors, with correspondingly lower t statistics.
b) Unexpected changes in coefficient magnitudes or signs.
c) Non significant coefficients despite a high R2."

To check for the problem of multicollinearity, Pearson Correlation Matrix was run and the result was presented in the following table.

Table 8. Pearson Correlation Matrix

	C1	C2	C3	A1	A2	A3	M1	M2	E1	E2	E3	E4	E5	E6	E7	E8	L1	L2	L3
C1	1																		
C2	.725**	1																	
C3	.959**	.730**	1																
A1	-.279**	-.155**	-.250**	1															
A2	-.461**	-.302**	-.374**	.537**	1														
A3	-.185**	-.145*	-.149**	0.011	.136*	1													
M1	-.048	-.008	-.030	.040	.104	.046	1												
M2	.004	.025	-.033	.271**	-.060	-.223**	-.150**	1											
E1	.283**	.194**	.215**	-.424**	-.451**	.257**	-.152**	-0.06	1										
E2	.284**	.183**	.223**	-.386**	-.655**	.315**	-.129*	-0.06	.897**	1									
E3	.050	-.034	.037	-.165**	-.065	-0.1	.052	-.263**	.070	.074	1								
E4	.246**	.168**	.164**	-.289**	-.468**	-.232**	.369**	0.093	.589**	.516**	.096	1							
E5	-.129*	-.181**	-.162**	-.096	-.070	0.007	-.059	.429**	.168**	.165**	.114*	.108	1						
E6	-.128*	-.076	-.099	.319**	.324**	-.527**	.098	.147**	-.826**	-.854**	-.081	-.400**	-.157**	1					
E7	-.060	.056	-.075	.286**	-.007	-.196**	-.057	.836**	-0.09	-0.07	-.181**	.050	.621**	.138*	1				
E8	.192**	0.088	0.074	-.201**	-.354**	-.202**	-.179**	.150**	.524**	.376**	.094	.639**	.068	-.187**	0.056	1			
L1	.592**	.572**	.598**	.001	-.184**	-.165**	-.090	.046	.300**	.206**	-.122*	.199**	-.268**	-.089	-.052	.169**	1		
L2	-.362**	-.561**	-.354**	-.070	.214**	.271**	.007	-.241**	-.242**	-.156**	.066	-.314**	.069	.030	-.327**	-.239**	-.603**	1	
L3	-.127*	-.389**	-.119*	-.146*	.069	.218**	-.047	-.172**	-0.1	-0.03	-.022	-.197**	.022	-.038	-.303**	-.133*	-.420**	.891**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Number of Observations- 308

When a correlation analysis was executed, virtually all of the variables were found to have pair-wise correlation coefficients that are at least significant at 5% confidence interval. Some of the independent variables have inflated correlation, as shown by the shaded cells with the correlation value of more than 0.7. The high interaction among the variables may obscure the individual contribution to the fit of the regression, whereas their joint effect may still be significant. It is important to minimize the problem of multicollinearity in order to receive acceptable results. It could be done by either manually removing highly correlated variables or running few different models. PCA, Backward, Forward and Stepwise methods) have the power of removing explanatory variables that are strongly correlating with each another (Hosmer & Lemeshow, 2000).

4.2. Logistic Regression Analysis

Forward Stepwise (Likelihood Ratio) selection method has been selected to determine the important variables with respect to their contributions in explaining bank failure. This technique was particularly useful because it only enters independent variables that significantly contribute to the model based on the Likelihood Ratio test, and avoids the above multicollinearity problems as a result of the inclusion of many variables (Vittinghoff et al, 2005, p.151). In addition, the likelihood-ratio test is more powerful than the Wald test, especially for small sample sizes (Vittinghoff et al 2005, p.173). Care, however, was taken for the variables' coefficients to be significant at 5% confidence interval, for the sign of each variable's coefficient to be in accordance with the one stated in the hypothesis and finally for the model to provide high classification results.

4.3. Selection of Predictor Variables

In Forward Stepwise (Likelihood Ratio) selection method, the probability used as a criterion to include the variable into the model is equal to 0.05, while the probability used to remove the variable from the model is equal to 0.10, and the cutoff point was set to be equal to 0.5.

The Beginning Block evaluates our model with only the constant in the equation (sometimes called the Null Model or baseline model). The constant is analogous to the y-intercept in OLS regression. The iteration history was specified. The first Iteration History table shows that estimation was terminated at iteration # 3 because the parameter estimates did not change by more than 0.001. The -2 Log likelihood (-2LL) is a likelihood ratio and represents the unexplained variance in the outcome variable. Therefore, the higher the value, the poorer the Null Model fits.

Table 9. Iteration History[a,b,c]

Iteration		-2 Log Likelihood (-2LL)	Coefficients
			Constant
Step 0	1	399.099	-.597
	2	399.074	-.616
	3	399.074	-.616

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 399.074

c. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Table 10 describes the Null Model or the baseline model– that is a model that does not include any explanatory variables. The Null Model is capable of accurately predicting 65%. The predictions of this baseline model are made purely on whichever category occurred most often in our dataset. In this data set the model always guesses 'Non-failed Bank' because more banks in the sample did not fail (200 non-failed banks compared to 108 failed banks).

Table 10. Classification Table[a,b]

Observed			**Predicted**		
			Failed or Non-Failed Bank		Percentage Correct
			Non-failed Bank	Failed Bank	
Step 0	Failed or Non-Failed Bank	Non-failed Bank	200	0	100%
		Failed Bank	108	0	0%
	Overall Classification		**308**	**0**	**65%**

a. Constant is included in the model.

b. The cut value is .500

Table 11 shows the logistic coefficient (B) associated with the intercept as it is included in the model. The Wald statistic is a chi-square type of statistic and is used to test the significance of the variable in the model. The Exp(B) refers to the change in odds ratio attributed to the variable. The interpretation of logit regression is different, since it assumes a non-linear relationship between probability and the independent variables. After taking the antilog of the estimated logit function (B), we get the odds ratios (Exp (B)). Therefore, Exp (B) should be considered the equivalent value when interpreting odds of bank failure.

Table 11. Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.616	.119	26.627	1	.000	.540

The Variables not in the Equation table (Table 12) simply lists the Wald test score, df, and sig. or p-value for each of the variables not included in the beginning block model. The Overall Statistics is not a total, but rather an estimate of overall Wald statistic associated with the model had all the variables been included in the model.

Table 12. Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	C1	83.528	1	.000
		C2	42.439	1	.000
		C3	59.265	1	.000
		A1	36.298	1	.000
		A2	72.132	1	.000
		A3	26.905	1	.000
		M1	2.255	1	.133
		M2	5.829	1	.016
		E1	75.053	1	.000
		E2	50.954	1	.000
		E3	10.219	1	.001
		E4	80.987	1	.000
		E5	3.927	1	.048
		E6	11.907	1	.001
		E7	11.892	1	.001
		E8	75.305	1	.000
		L1	53.999	1	.000
		L2	41.975	1	.000
		L3	15.903	1	.000
	Overall Statistics		**196.808**	**19**	**.000**

Now we move to the regression model that includes our explanatory variables. The next set of tables begins with the heading of **Block 1: Method = Forward Stepwise (Likelihood Ratio).**

During its initial forward stepwise method, the model started with only one variable entered (C1). Then each variable will be added for the next step based on its contribution in the magnitude change in -2LL ratio from one step to next step. The one with the maximum contribution in the magnitude change in -2LL ratio will be added first in the next step. The last step has the final important variable in the model. The following variables were included in the 7th step: C1, M2, L1, L2 and E1 based on the likelihood test using forward stepwise procedure as shown in Table 7. Detail of the iteration history is annexed. The Iteration History table shows that estimation was terminated at iteration number 7 because the parameter estimates did not change by more than 0.001. In the same table, the -2LL is a likelihood ratio and represents the unexplained variance in the outcome variable. Therefore, the smaller the value, the better the fit of the model. Notice here the -2LL (121.554) is substantially lower than that of the null model (399.074).

Table 13. Iteration History[a,b,c,d,e,f]

Iteration		-2 Log Likelihood	Coefficients					
			Constant	C1	M2	L2	L1	E1
Step 7	1	238.605	-1.247	-.123	.062	.023	.001	-.138
	2	161.417	-.904	-.231	.136	.020	-.005	-.381
	3	133.516	-.763	-.337	.222	.022	-.019	-.577
	4	124.616	-.544	-.429	.285	.025	-.042	-.705
	5	121.991	-.329	-.481	.314	.027	-.071	-.781
	6	121.562	-.219	-.503	.325	.028	-.090	-.822
	7	121.554	-.205	-.507	.327	.029	-.093	-.829
	8	121.554	-.205	-.507	.327	.029	-.093	-.830

a. Method: Forward Stepwise (Likelihood Ratio)
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 399.074
d. Estimation terminated at iteration step 7 because parameter estimates changed by less than .001.

The Omnibus Tests of Model Coefficients in Table 14 is used to check that the new model (with explanatory variables included) is an improvement over the baseline model or the Null Model. It uses chi-square tests to see if there is a significant difference between the Log-likelihoods (specifically the -2LL) of the baseline model and the new model. The table reports the chi-square associated with the last step in a forward stepwise model. The significance value or p-value indicates our model is significantly different from the constant only model (Null Model); meaning there is a significant effect for the combined predictors on the outcome variable. In other words, the Sig. values are $p < .001$, which indicates the accuracy of the model improves when we add our explanatory variables.

Table 14. Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 7[a]	Step	-.072	1	.789
	Block	277.521	5	.000
	Model	277.521	5	.000

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Also based on score test, fourteen variables were removed from the model in the 7th step of iteration as shown in the Table 15 due to the fact that the score statistics for all variables are not significant. At 0.05 level of significance and based on the results of likelihood ratio test and the score test, there is a sufficient evidence that only the following variables C1, M2, L1, L2 and E1 are very important in explaining bank failure.

Table 15. Variables not in the Equation

			Score	df	Sig.
Step 7[a]	Variables	C2	1.273	1	.259
		C3	1.024	1	.312
		A1	1.260	1	.262
		A2	.494	1	.482
		A3	.126	1	.723
		M1	.037	1	.847
		E2	.107	1	.744
		E3	.040	1	.842
		E4	.108	1	.743
		E5	.931	1	.335
		E6	.165	1	.684
		E7	3.244	1	.072
		E8	.427	1	.513
		L3	.074	1	.786
	Overall Statistics		5.652	14	.975

a. Variable(s) removed on step 7: E4.

4.4. Hosmer and Lemeshow Test

The Hosmer and Lemeshow Test table is to test the goodness-of-fit of the model. The test which is used to measure R^2, is not truly R^2 estimates; they are pseudo-R^2. The R^2 values tell us approximately how much variation in the outcome is explained by the model (Hosmer & Lemeshow, 2000). The Chi-square of Hosmer is equal to 3.634 and the p-value associated with the test is equal to 0.889; which suggests that the model explains roughly 89% of the variation in the outcome. Since the p-value exceeds 0.05 I rejected the null hypothesis that states the observed and the predicted values of the response variable are not statistically differ. Therefore, we can conclude that the model fits the data very well.

Table 16. Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.031	8	.430
2	12.637	8	.125
3	5.363	8	.718
4	6.978	8	.539
5	4.644	8	.795
6	3.557	8	.895
7	3.634	8	.889

4.5. The Predicted Logit Model

In this sub-section we will discuss the estimation results and highlight the coefficients which are found to be statistically significant form the cross-country model. As mentioned, SPSS is predicting the likelihood of the dependant variable being a 1, in this case “failed bank”. When the odds ratio is less than 1, increasing values in the variable correspond to decreasing odds of bank failure occurrence. When the odds ratio is greater than 1, increasing values of the variable corresponds to increasing odds of bank failure occurrence.

Table 17. Variables in the Equation

a,b,c,d,e,f,g		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I for EXP(B)	
								Lower	Upper
Step 7	C1	-.507	.108	21.939	1	.000	.602	.487	.745
	M2	.327	.073	20.012	1	.000	1.387	1.202	1.601
	E1	-.830	.160	26.968	1	.000	.436	.319	.597
	L1	-.093	.038	6.097	1	.014	.912	.847	.981
	L2	.029	.017	3.022	1	.082	1.029	.996	1.063
	Constant	-.205	1.264	.026	1	.871	.815		

a. Variable(s) entered on step 1: C1.
b. Variable(s) entered on step 2: E4.
c. Variable(s) entered on step 3: M2.
d. Variable(s) entered on step 4: L2.
e. Variable(s) entered on step 5: L1.
f. Variable(s) entered on step 6: E1.
g. Variable(s) removed on step 7: E4.

From the Forward Stepwise (Likelihood Ratio), which are created by pooling the covariates of the three countries in one series, the researcher single out four coefficients which are found to be significant at 5%. These are the coefficients for capital to total assets ratio (C1), Gross Yield on Assets (M2), ROA (E1), and Cash & Bank Balance (L1). The empirical evidence is corroborated by repeated bank failure prediction model studied by different scholar as summarized by Table 2 in the literature part.

Interestingly, the model identified four out of five variables that represent each categories of CAMEL. Results also show that C1, E1 & L1 are negatively associated with the probability of failure. These results are consistent with my expectations. Likewise, the sign of the measure of a bank’s loan to asset ratio (L2) also corresponds to my expectation, though it is insignificant. On the other hand covariate M2 was found to exhibit the unexpected sign. Opposite to theoretical, the coefficient of Gross Yield on Assets (M2), which is calculated by dividing total income by total assets, has a positive sign. The positive sign in M2 ratio can be explained probably by two reinforcing results. On the denominator side of the formula, when bank are on the verge of failure they basically face liquidity problem; fast draining their asset base. On the numerator side, since the bank is on the going concern it keeps record earning or recognize income. As a result, the massive decline in the denominator coupled with the relatively stable balance in the numerator will make the M2 ratio to be misleadingly inflated.

4.6. Relationship of Individual Independent Variables to Bank Failure

The results on capital to asset ratio (C1) demonstrate the negative significance (at 1% level). The value of Exp(B) was 0.602 which implies that for each unit increase in C1 the odds of failure decreased by 39.8% (0.602 - 1.0 = -0.398). Result could indicate that better capitalized banks have more opportunities to cover their losses and meet obligations in case of bankruptcy.

The results on GYoA ratio (M2) demonstrate the positive significance (at 1% level). The value of Exp(B) was 1.387 which implies that for each unit increase in M2 the odds of failure increased by 38.7% (1.387 - 1.0 = 0.387).

The results on ROA ratio (E1) demonstrate the negative significance (at 1% level). The value of Exp(B) was 0.436 which implies that for each unit increase in E1 the odds of failure decrease by 56.4% (0.436 - 1.0 = -0.564). Influence of the ROA on the bank default prediction is highly significant. According to the theoretical expectations has the same direction of influence. This result is in line with the result of Altman (1968), Thomson (1991), Lanine and Vennet (2006), Andersen (2008), Boyacioglu (2009) & Adeyeye (2015) who found that this coefficient contributes the most to the possibility of prediction the incidence of bank failure, since a bank that does not earn a profit has higher probability to failure.

The results on Cash & Bank Balance ratio (L1) demonstrate the negative significance (at 5% level). The value of Exp(B) was 0.912 which implies that for each unit increase in E1 the odds of failure decrease by 8.8% (0.912 - 1.0 = -0.088). Thomson (1991), Nurazi (2005) & Andersen (2008) empirically found out that this coefficient has high degree of predicting bank failure.

Table 18. Relationship of independent variable to bank failure

a,b,c,d,e,f,g		B	Sig.	Exp(B)
Step 7	C1	-.507	.000	.602
	M2	.327	.000	1.387
	E1	-.830	.000	.436
	L1	-.093	.014	.912
	L2	.029	.082	1.029
	Constant	-.205	.871	.815

4.7. Validating the Hypothesis

At the outset it was hypothesized that bank specific factors using selected CAMEL are statistically significant in predicting bank failure. As presented in Table 17, bank specific factors are significant in predicting bank failure. The above results thus leads to the rejection of **H0 Hypotheses** that there is no significant effect from capital adequacy, management ability, earning and liquidity in predicting bank failure. Unfortunately, we have to accept the **H0 Hypothesis** that say there is no significant effect from asset quality in predicting bank failure. However, we should note that, if it wasn't for the absence of NPL data for each bank, the result would have been changed.

4.8. Classification Accuracy of the Model

The next step is to determine the predictive accuracy of the empirical estimations by comparing predicted outcome with the actual outcome. Table 18 displays the relationship between model predictions and actual distress events. Using a cutoff value of 0.5, the model was able to correctly predict of 88% of the periods in which banks were expected to go into failure and 94% of periods in which banks were expected to be financially stable. The model failed to classify correctly 13 failed banks out of 108 (12% Type 1 Error) compared to wrongly classified 13 healthy banks out of 200 as failed banks (7% Type II Error). The overall predictability accuracy of the logistic regression model was 92%, which is pretty much high.

Table 19. Classification Table[a]

Observed			Predicted		
			Failed or Non-Failed Bank		Percentage Correct
			Non-failed Bank	Failed Bank	
Step 7	Failed or Non-Failed Bank	Non-failed Bank	187	13	93.5%
		Failed Bank	13	95	88.0%
	Overall Percentage				**92%**

a. The cut value is .500

SPSS produces two statistics that are roughly equivalent in interpretation to the R2 in linear regression: Cox and Snell's R2 and Nagelkerke's R2. Nagelkerke's R2 is an improvement of Cox and Snell's R2 that can attain a value of one when the model predicts the data perfectly. Nagelkerke's R2 reported 0.818 which means that the model explains 81.8% of the variation in data one year prior to actual failure.

Table 20. Model Summary

Step	-2 Log Likelihood (-2LL)	Cox & Snell R Square	Nagelkerke R Square
1	246.909[a]	.390	.537
2	175.433[b]	.516	.711
3	146.089[b]	.560	.771
4	136.300[b]	.574	.790
5	128.430[c]	.585	.805
6	121.482[c]	.594	.818
7	121.554[c]	.594	.818

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

c. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Chapter V

5. Conclusion & Recommendations

5.1. Conclusion

The banking crises across the globe have demonstrated the interconnection of financial systems and the economy as a whole, both within and across countries. A disruption in one financial sector is scattering rapidly to others, thereby threatening the whole system. Because of the knock-on effects of bank failure supervisions are intended to identify and address problems as they emerge, to avert failure when possible, and to make failures less costly when they do occur.

One of the major motivations for this study was the non-existence of research on bank failure prediction in Ethiopia. To develop bank failure prediction model for Ethiopia, we don't have to wait for actual failure to happen. Instead failure situation in other countries can provide us a useful benchmark to easily identifying banks with high and increasing probabilities of failure proactively. This kind of research could supply invaluable information by examine the factors and parameters that are important and significant in the forecast of bank failure for the Ethiopian banking industry.

Against this backdrop, the researcher developed baseline bank failure prediction model for the Ethiopian banking industry using Turkish and U.S bank failure experience. A logistic regression was performed using nineteen bank specific CAMEL ratios on the likelihood of bank failure.

Only four out of the nineteen CAMEL ratios were found to be significant in predicting banks that will face failure one year prior to actual failure. To be specific, C1, representing capital adequacy, has a negative and significant impact on bank failure. E1, as reflected by ROA, is also an important determinant of bank failure. Moreover, L1, measure of cash & bank balance to total asset, is significantly and negatively related to default probabilities. On the other hand, M2, which measures GYoA, are found to be positively correlated with failure. The overall predictive power of the model (92%) was quite high, while the significant Chi square ($P < 0.01$) was indicative of the strength of the joint effect of the covariates in predicting bank failure. Most of the significant variables that I have found empirical were corroborated by the finding of many scholars on bank failure prediction model.

Using empirical cross-country study, the Logit produced the following baseline bank failure prediction model:

$$\begin{aligned}&Ln\ [Probability\ of\ Failure/\\ &Probability\ of\ Non\text{-}failure] = -.25 - .507(C_1) + .327(M_2) - .830(E_1) - .093\ (L_1)\end{aligned}$$

5.2. Recommendations

The following recommendations are forwarded based on my finding.

- In search for resilient financial sector in Ethiopia, adopting the cross-country baseline bank failure prediction model, with its forward looking nature, will have a paramount importance to regulators and policy makers by providing information on potentially vulnerable banks or would-be failed banks, thereby preventing potential financial contagion and systemic banking crises ahead.

- Conduct stress tests on the developed model to estimate the effect of specific shocks on bank's soundness. Therefore, assessing potentials of financial institutions to withstand such shocks by applying it in to the derived model is useful in providing early warning information, which could be used to devise policy measures to reduce bank failure. The shocks to include in the model are: decline in net-interest margin, increase in non-performing loans, decline in liquidity, deterioration in capital adequacy, and decline in earning etc…..

- Events of numerous financial crises and their negative repercussion effect to the wider economy across the globe have demonstrated the importance of effective deposit protection scheme. In this regard, the government of Ethiopia shall establish a deposit insurance institution for protecting depositors and maintaining the stability of the financial system. The presence of deposit insurance maintains a high degree of financial stability especially during the crisis time by stalling or minimizing 'run on banks'.

- As empirically proven, those banks that are on the verge of collapse virtually run out of liquidity. Thus, I recommend that the government should develop domestic capital market in order to ease the liquidity problem.

- For future work, it is worth noting to have a combination of other models, including Neutral Networks, in tandem with logit model to have a combination of robust models with high and better predictive power.

- While this study is all about bank failure prediction model, the framework developed in this paper provides an ideal setting to adapt to other sectors, including insurances and micro-finances.

- Unfortunately, this paper did not take into consideration some factors, such as country specific macroeconomic variables and other additional bank specific variables. Hence, the model would then provide more insights in predicting future bank failure under different scenarios. So I invite other interested researcher to fill these gaps.

- Another line of future work could be made by considering additional countries' failed bank experience, especially from developing countries, by looking out for any additional significant variables capable of predict bank failure.

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WEBSITES

- *www.worldbank.org/*
- *www.fdic.gov/*
- *www.tbb.org.tr/en/*

Annex I- Logit Model Results

Correlations Matrix

		C1	C2	C3	A1	A2	A3	M1	M2	E1	E2	E3	E4	E5	E6	E7	E8	L1	L2	L3
C1	Pearson Correlation	1	.725**	.959**	-.279**	-.461**	-.185**	-.048	.004	.283**	.284**	.050	.246**	-.129*	-.128*	-.060	.192**	.592**	-.362**	-.127*
	Sig. (2-tailed)		*.000*	*.000*	*.000*	*.000*	*.001*	*.406*	*.947*	*.000*	*.000*	*.385*	*.000*	*.024*	*.025*	*.297*	*.001*	*.000*	*.000*	*.026*
C2	Pearson Correlation	.725**	1	.730**	-.155**	-.302**	-.145*	-.008	.025	.194**	.183**	-.034	.168**	-.181**	-.076	.056	.088	.572**	-.561**	-.389**
	Sig. (2-tailed)	*.000*		*.000*	*.007*	*.000*	*.011*	*.895*	*.664*	*.001*	*.001*	*.557*	*.003*	*.001*	*.182*	*.328*	*.125*	*.000*	*.000*	*.000*
C3	Pearson Correlation	.959**	.730**	1	-.250**	-.374**	-.149**	-.030	-.033	.215**	.223**	.037	.164**	-.162**	-.099	-.075	.074	.598**	-.354**	-.119*
	Sig. (2-tailed)	*.000*	*.000*		*.000*	*.000*	*.009*	*.601*	*.570*	*.000*	*.000*	*.521*	*.004*	*.004*	*.084*	*.192*	*.192*	*.000*	*.000*	*.036*
A1	Pearson Correlation	-.279**	-.155**	-.250**	1	.537**	0.011	.040	.271**	-.424**	-.386**	-.165**	-.289**	-.096	.319**	.286**	-.201**	.001	-.070	-.146*
	Sig. (2-tailed)	*.000*	*.007*	*.000*		*.000*	*.845*	*.487*	*.000*	*.000*	*.000*	*.004*	*.000*	*.091*	*.000*	*.000*	*.000*	*.980*	*.221*	*.010*
A2	Pearson Correlation	-.461**	-.302**	-.374**	.537**	1	.136*	.104	-.060	-.451**	-.655**	-.065	-.468**	-.070	.324**	-.007	-.354**	-.184**	.214**	.069
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.000*		*.017*	*.068*	*.297*	*.000*	*.000*	*.257*	*.000*	*.219*	*.000*	*.901*	*.000*	*.001*	*.000*	*.227*
A3	Pearson Correlation	-.185**	-.145*	-.149**	0.011	.136*	1	.046	-.223**	.257**	.315**	-0.1	-.232**	0.007	-.527**	-.196**	-.202**	-.165**	.271**	.218**
	Sig. (2-tailed)	*.001*	*.011*	*.009*	*.845*	*.017*		*.424*	*.000*	*.000*	*.000*	*.082*	*.000*	*.905*	*.000*	*.001*	*.000*	*.004*	*.000*	*.000*
M1	Pearson Correlation	-.048	-.008	-.030	.040	.104	.046	1	-.150**	-.152**	-.129*	.052	.369**	-.059	.098	-.057	-.179**	-.090	.007	-.047
	Sig. (2-tailed)	*.406*	*.895*	*.601*	*.487*	*.068*	*.424*		*.008*	*.008*	*.023*	*.363*	*.000*	*.299*	*.085*	*.320*	*.002*	*.115*	*.908*	*.416*
M2	Pearson Correlation	.004	.025	-.033	.271**	-.060	-.223**	-.150**	1	-0.06	-0.06	-.263**	0.093	.429**	.147**	.836**	.150**	.046	-.241**	-.172**
	Sig. (2-tailed)	*.947*	*.664*	*.570*	*.000*	*.297*	*.000*	*.008*		*.317*	*.311*	*.000*	*.103*	*.000*	*.010*	*.000*	*.008*	*.423*	*.000*	*.003*
E1	Pearson Correlation	.283**	.194**	.215**	-.424**	-.451**	.257**	-.152**	-0.06	1	.897**	.070	.589**	.168**	-.826**	-0.09	.524**	.300**	-.242**	-0.1
	Sig. (2-tailed)	*.000*	*.001*	*.000*	*.000*	*.000*	*.000*	*.008*	*.317*		*.000*	*.218*	*.000*	*.003*	*.000*	*.105*	*.000*	*.000*	*.000*	*.074*
E2	Pearson Correlation	.284**	.183**	.223**	-.386**	-.655**	.315**	-.129*	-0.06	.897**	1	.074	.516**	.165**	-.854**	-0.07	.376**	.206**	-.156**	-0.03
	Sig. (2-tailed)	*.000*	*.001*	*.000*	*.000*	*.000*	*.000*	*.023*	*.311*	*.000*		*.193*	*.000*	*.004*	*.000*	*.201*	*.000*	*.000*	*.006*	*.587*
E3	Pearson Correlation	.050	-.034	.037	-.165**	-.065	-0.1	.052	-.263**	.070	.074	1	.096	.114*	-.081	-.181**	.094	-.122*	.066	-.022
	Sig. (2-tailed)	*.385*	*.557*	*.521*	*.004*	*.257*	*.082*	*.363*	*.000*	*.218*	*.193*		*.092*	*.045*	*.155*	*.001*	*.101*	*.033*	*.245*	*.705*
E4	Pearson Correlation	.246**	.168**	.164**	-.289**	-.468**	-.232**	.369**	0.093	.589**	.516**	.096	1	.108	-.400**	.050	.639**	.199**	-.314**	-.197**
	Sig. (2-tailed)	*.000*	*.003*	*.004*	*.000*	*.000*	*.000*	*.000*	*.103*	*.000*	*.000*	*.092*		*.059*	*.000*	*.382*	*.000*	*.000*	*.000*	*.001*
E5	Pearson Correlation	-.129*	-.181**	-.162**	-.096	-.070	0.007	-.059	.429**	.168**	.165**	.114*	.108	1	-.157**	.621**	.068	-.268**	.069	.022
	Sig. (2-tailed)	*.024*	*.001*	*.004*	*.091*	*.219*	*.905*	*.299*	*.000*	*.003*	*.004*	*.045*	*.059*		*.006*	*.000*	*.236*	*.000*	*.228*	*.701*
E6	Pearson Correlation	-.128*	-.076	-.099	.319**	.324**	-.527**	.098	.147**	-.826**	-.854**	-.081	-.400**	-.157**	1	.138*	-.187**	-.089	.030	-.038
	Sig. (2-tailed)	*.025*	*.182*	*.084*	*.000*	*.000*	*.000*	*.085*	*.010*	*.000*	*.000*	*.155*	*.000*	*.006*		*.015*	*.001*	*.120*	*.599*	*.503*
E7	Pearson Correlation	-.060	.056	-.075	.286**	-.007	-.196**	-.057	.836**	-0.09	-0.07	-.181**	.050	.621**	.138*	1	.056	-.052	-.327**	-.303**
	Sig. (2-tailed)	*.297*	*.328*	*.192*	*.000*	*.901*	*.001*	*.320*	*.000*	*.105*	*.201*	*.001*	*.382*	*.000*	*.015*		*.331*	*.362*	*.000*	*.000*
E8	Pearson Correlation	.192**	.088	.074	-.201**	-.354**	-.202**	-.179**	.150**	.524**	.376**	.094	.639**	.068	-.187**	.056	1	.169**	-.239**	-.133*
	Sig. (2-tailed)	*.001*	*.125*	*.192*	*.000*	*.000*	*.000*	*.002*	*.008*	*.000*	*.000*	*.101*	*.000*	*.236*	*.001*	*.331*		*.003*	*.000*	*.020*
L1	Pearson Correlation	.592**	.572**	.598**	.001	-.184**	-.165**	-.090	.046	.300**	.206**	-.122*	.199**	-.268**	-.089	-.052	.169**	1	-.603**	-.420**
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.980*	*.001*	*.004*	*.115*	*.423*	*.000*	*.000*	*.033*	*.000*	*.000*	*.120*	*.362*	*.003*		*.000*	*.000*
L2	Pearson Correlation	-.362**	-.561**	-.354**	-.070	.214**	.271**	.007	-.241**	-.242**	-.156**	.066	-.314**	.069	.030	-.327**	-.239**	-.603**	1	.891**
	Sig. (2-tailed)	*.000*	*.000*	*.000*	*.221*	*.000*	*.000*	*.908*	*.000*	*.000*	*.006*	*.245*	*.000*	*.228*	*.599*	*.000*	*.000*	*.000*		*.000*
L3	Pearson Correlation	-.127*	-.389**	-.119*	-.146*	.069	.218**	-.047	-.172**	-0.1	-0.03	-.022	-.197**	.022	-.038	-.303**	-.133*	-.420**	.891**	1
	Sig. (2-tailed)	*.026*	*.000*	*.036*	*.010*	*.227*	*.000*	*.416*	*.003*	*.074*	*.587*	*.705*	*.001*	*.701*	*.503*	*.000*	*.020*	*.000*	*.000*	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	308	100%
	Missing Cases	0	0.0
	Total	**308**	**100%**
Unselected Cases		0	0.0
Total		**308**	**100%**

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Non-failed Bank	0
Failed Bank	1

Iteration History[a,b,c,d,e,f]

Iteration		-2 Log likelihood	Coefficients						
			Constant	C1	E4	M2	L2	L1	E1
Step 1	1	300.582	1.100	-.179					
	2	256.749	2.525	-.373					
	3	247.478	3.450	-.506					
	4	246.912	3.746	-.549					
	5	246.909	3.769	-.553					
	6	246.909	3.769	-.553					
Step 2	1	246.672	.706	-.144	-.010				
	2	190.098	1.184	-.236	-.022				
	3	176.949	1.719	-.318	-.031				
	4	175.464	2.028	-.362	-.035				
	5	175.433	2.086	-.370	-.036				
	6	175.433	2.088	-.370	-.036				
	7	175.433	2.088	-.370	-.036				
Step 3	1	233.676	.207	-.143	-.010	.066			
	2	165.242	.118	-.232	-.025	.138			
	3	148.430	.236	-.319	-.035	.194			
	4	146.162	.356	-.372	-.040	.225			
	5	146.089	.386	-.386	-.041	.234			
	6	146.089	.387	-.386	-.041	.234			
	7	146.089	.387	-.386	-.041	.234			
Step 4	1	227.562	-1.099	-.126	-.009	.080	.018		
	2	158.878	-1.395	-.228	-.023	.155	.023		
	3	140.071	-1.714	-.341	-.031	.216	.032		
	4	136.530	-1.979	-.435	-.034	.255	.041		
	5	136.302	-2.103	-.468	-.035	.269	.045		
	6	136.300	-2.116	-.470	-.035	.270	.045		
	7	136.300	-2.116	-.470	-.035	.270	.045		
Step 5	1	226.770	-.835	-.115	-.009	.078	.015	-.006	
	2	157.517	-.952	-.216	-.022	.152	.017	-.010	
	3	136.585	-.771	-.329	-.030	.208	.022	-.022	
	4	130.254	-.418	-.432	-.032	.243	.026	-.044	
	5	128.627	-.210	-.480	-.034	.257	.029	-.068	
	6	128.432	-.124	-.495	-.035	.261	.030	-.080	
	7	128.430	-.115	-.497	-.035	.262	.030	-.081	
	8	128.430	-.114	-.497	-.035	.262	.030	-.081	
Step 6	1	222.591	-.921	-.112	-.007	.071	.015	-.003	-.069
	2	155.556	-1.002	-.211	-.016	.147	.017	-.007	-.144
	3	133.274	-.844	-.323	-.014	.216	.021	-.020	-.349
	4	124.491	-.548	-.428	.001	.284	.025	-.043	-.717
	5	121.889	-.323	-.484	.002	.318	.027	-.072	-.824
	6	121.489	-.219	-.507	.002	.331	.028	-.090	-.871

	7	121.482	-.207	-.511	.002	.333	.029	-.093	-.879
	8	121.482	-.207	-.511	.002	.333	.029	-.093	-.879
Step 7	1	238.605	-1.247	-.123		.062	.023	.001	-.138
	2	161.417	-.904	-.231		.136	.020	-.005	-.381
	3	133.516	-.763	-.337		.222	.022	-.019	-.577
	4	124.616	-.544	-.429		.285	.025	-.042	-.705
	5	121.991	-.329	-.481		.314	.027	-.071	-.781
	6	121.562	-.219	-.503		.325	.028	-.090	-.822
	7	121.554	-.205	-.507		.327	.029	-.093	-.829
	8	121.554	-.205	-.507		.327	.029	-.093	-.830

a. Method: Forward Stepwise (Likelihood Ratio)
b. Constant is included in the model.
c. Initial -2 Log Likelihood: 399.074
d. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.
e. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.
f. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	152.165	1	.000
	Block	152.165	1	.000
	Model	152.165	1	.000
Step 2	Step	71.475	1	.000
	Block	223.641	2	.000
	Model	223.641	2	.000
Step 3	Step	29.344	1	.000
	Block	252.985	3	.000
	Model	252.985	3	.000
Step 4	Step	9.789	1	.002
	Block	262.774	4	.000
	Model	262.774	4	.000
Step 5	Step	7.871	1	.005
	Block	270.645	5	.000
	Model	270.645	5	.000
Step 6	Step	6.948	1	.008
	Block	277.592	6	.000
	Model	277.592	6	.000
Step 7[a]	Step	-.072	1	.789
	Block	277.521	5	.000
	Model	277.521	5	.000

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	246.909[a]	.390	.537
2	175.433[b]	.516	.711
3	146.089[b]	.560	.771
4	136.300[b]	.574	.790
5	128.430[c]	.585	.805
6	121.482[c]	.594	.818
7	121.554[c]	.594	.818

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.
b. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.
c. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Variables in the Equation									
		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	C1	-.553	.065	72.564	1	.000	.575	.507	.653
	Constant	3.769	.505	55.774	1	.000	43.342		
Step 2[b]	C1	-.370	.073	26.097	1	.000	.690	.599	.796
	E4	-.036	.006	41.189	1	.000	.965	.954	.975
	Constant	2.088	.592	12.434	1	.000	8.067		
Step 3[c]	C1	-.386	.080	23.406	1	.000	.680	.581	.795
	M2	.234	.065	13.041	1	.000	1.264	1.113	1.435
	E4	-.041	.006	45.159	1	.000	.959	.948	.971
	Constant	.387	.701	.305	1	.581	1.473		
Step 4[d]	C1	-.470	.098	23.174	1	.000	.625	.516	.757
	M2	.270	.061	19.302	1	.000	1.310	1.161	1.478
	E4	-.035	.006	31.035	1	.000	.965	.954	.977
	L2	.045	.016	8.492	1	.004	1.047	1.015	1.079
	Constant	-2.116	1.172	3.261	1	.071	.120		
Step 5[e]	C1	-.497	.103	23.276	1	.000	.608	.497	.744
	M2	.262	.063	17.489	1	.000	1.299	1.149	1.469
	E4	-.035	.007	28.315	1	.000	.966	.953	.978
	L1	-.081	.035	5.279	1	.022	.922	.860	.988
	L2	.030	.016	3.629	1	.057	1.031	.999	1.064
	Constant	-.114	1.265	.008	1	.928	.892		
Step 6[f]	C1	-.511	.110	21.779	1	.000	.600	.484	.743
	M2	.333	.077	18.900	1	.000	1.395	1.201	1.621
	E1	-.879	.224	15.462	1	.000	.415	.268	.644
	E4	.002	.007	.105	1	.746	1.002	.989	1.016
	L1	-.093	.038	6.146	1	.013	.911	.846	.981
	L2	.029	.016	3.047	1	.081	1.029	.996	1.063
	Constant	-.207	1.257	.027	1	.869	.813		
Step 7[f]	C1	-.507	.108	21.939	1	.000	.602	.487	.745
	M2	.327	.073	20.012	1	.000	1.387	1.202	1.601
	E1	-.830	.160	26.968	1	.000	.436	.319	.597
	L1	-.093	.038	6.097	1	.014	.912	.847	.981
	L2	.029	.017	3.022	1	.082	1.029	.996	1.063
	Constant	-.205	1.264	.026	1	.871	.815		

a. Variable(s) entered on step 1: C1.
b. Variable(s) entered on step 2: E4.
c. Variable(s) entered on step 3: M2.
d. Variable(s) entered on step 4: L2.
e. Variable(s) entered on step 5: L1.
f. Variable(s) entered on step 6: E1.

Classification Table[a]

Observed			Predicted: Failed or Non-Failed Bank: Non-failed Bank	Predicted: Failed or Non-Failed Bank: Failed Bank	Predicted: Percentage Correct
Step 1	Failed or Non-Failed Bank	Non-failed Bank	181	19	90.5%
		Failed Bank	32	76	70.4%
	Overall Percentage				**83%**
Step 2	Failed or Non-Failed Bank	Non-failed Bank	186	14	93.0%
		Failed Bank	25	83	76.9%
	Overall Percentage				**87%**
Step 3	Failed or Non-Failed Bank	Non-failed Bank	188	12	94.0%
		Failed Bank	18	90	83.3%
	Overall Percentage				**90%**
Step 4	Failed or Non-Failed Bank	Non-failed Bank	187	13	93.5%
		Failed Bank	14	94	87.0%
	Overall Percentage				**91%**
Step 5	Failed or Non-Failed Bank	Non-failed Bank	188	12	94.0%
		Failed Bank	12	96	88.9%
	Overall Percentage				**92%**
Step 6	Failed or Non-Failed Bank	Non-failed Bank	188	12	94.0%
		Failed Bank	13	95	88.0%
	Overall Percentage				**92%**
Step 7	Failed or Non-Failed Bank	Non-failed Bank	187	13	93.5%
		Failed Bank	13	95	88.0%
	Overall Percentage				**92%**

a. The cut value is .500

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	C1	-199.537	152.165	1	.000
Step 2	C1	-119.320	63.207	1	.000
	E4	-123.454	71.475	1	.000
Step 3	C1	-101.938	57.786	1	.000
	M2	-87.717	29.344	1	.000
	E4	-116.058	86.028	1	.000
Step 4	C1	-92.556	48.812	1	.000
	M2	-87.001	37.701	1	.000
	E4	-95.204	54.107	1	.000
	L2	-73.045	9.789	1	.002
Step 5	C1	-80.835	33.240	1	.000
	M2	-80.534	32.638	1	.000
	E4	-89.913	51.396	1	.000
	L1	-68.150	7.871	1	.005
	L2	-66.065	3.701	1	.054
Step 6	C1	-75.480	29.479	1	.000
	M2	-78.524	35.566	1	.000
	E1	-64.215	6.948	1	.008
	E4	-60.777	.072	1	.789
	L1	-65.144	8.807	1	.003
	L2	-62.277	3.072	1	.080
Step 7	C1	-75.572	29.590	1	.000
	M2	-79.170	36.787	1	.000
	E1	-89.913	58.272	1	.000
	L1	-65.147	8.740	1	.003
	L2	-62.302	3.051	1	.081

Annex II- List of US Failed Banks

S/N	U.S. Failed Banks	Date of Failure
1	Carson River Community Bank	February 26, 2010
2	Rainier Pacific Bank	February 26, 2010
3	George Washington Savings Bank	February 19, 2010
4	La Jolla Bank, FSB	February 19, 2010
5	Marco Community Bank	February 19, 2010
6	The La Coste National Bank	February 19, 2010
7	1st American State Bank of Minnesota	February 5, 2010
8	American Marine Bank	January 29, 2010
9	Community Bank and Trust	January 29, 2010
10	First National Bank of Georgia	January 29, 2010
11	First Regional Bank	January 29, 2010
12	Florida Community Bank	January 29, 2010
13	Marshall Bank, N.A.	January 29, 2010
14	Bank of Leeton	January 22, 2010
15	Charter Bank	January 22, 2010
16	Columbia River Bank	January 22, 2010
17	Evergreen Bank	January 22, 2010
18	Premier American Bank	January 22, 2010
19	Barnes Banking Company	January 15, 2010
20	St. Stephen State Bank	January 15, 2010
21	Town Community Bank & Trust	January 15, 2010
22	Horizon Bank	January 8, 2010
23	Valley Community Bank	February 25, 2011
24	Charter Oak Bank	February 18, 2011
25	Citizens Bank of Effingham	February 18, 2011
26	Habersham Bank	February 18, 2011
27	San Luis Trust Bank, FSB	February 18, 2011
28	Badger State Bank	February 11, 2011
29	Canyon National Bank	February 11, 2011
30	Peoples State Bank	February 11, 2011
31	Sunshine State Community Bank	February 11, 2011
32	American Trust Bank	February 4, 2011
33	Community First Bank Chicago	February 4, 2011
34	North Georgia Bank	February 4, 2011
35	Evergreen State Bank	January 28, 2011
36	First Community Bank	January 28, 2011
37	FirsTier Bank	January 28, 2011
38	The First State Bank	January 28, 2011
39	CommunitySouth Bank & Trust	January 21, 2011
40	Enterprise Banking Company	January 21, 2011
41	The Bank of Asheville	January 21, 2011
42	United Western Bank	January 21, 2011
43	Oglethorpe Bank	January 14, 2011
44	First Commercial Bank of Florida	January 7, 2011
45	Legacy Bank	January 7, 2011
46	Fidelity Bank	March 30, 2012
47	Covenant Bank & Trust	March 23, 2012

48	Premier Bank	March 23, 2012
49	New City Bank	March 9, 2012
50	Global Commerce Bank	March 2, 2012
51	Central Bank of Georgia	February 24, 2012
52	Home Savings of America	February 24, 2012
53	Charter National Bank and Trust	February 10, 2012
54	SCB Bank	February 10, 2012
55	BankEast	January 27, 2012
56	First Guaranty Bank and Trust Company of Jacksonville	January 27, 2012
57	Patriot Bank Minnesota	January 27, 2012
58	Tennessee Commerce Bank	January 27, 2012
59	American Eagle Savings Bank	January 20, 2012
60	Central Florida State Bank	January 20, 2012
61	The First State Bank	January 20, 2012
62	Central Arizona Bank	May 14, 2013
63	Pisgah Community Bank	May 10, 2013
64	Sunrise Bank	May 10, 2013
65	Douglas County Bank	April 26, 2013
66	Parkway Bank	April 26, 2013
67	Chipola Community Bank	April 19, 2013
68	First Federal Bank	April 19, 2013
69	Heritage Bank of North Florida	April 19, 2013
70	Gold Canyon Bank	April 5, 2013
71	Frontier Bank	March 8, 2013
72	Covenant Bank	February 15, 2013
73	1st Regents Bank	January 18, 2013
74	Westside Community Bank	January 11, 2013
75	The Freedom State Bank	June 27, 2014
76	Valley Bank	June 20, 2014
77	Valley Bank	June 20, 2014
78	Slavie Federal Savings Bank	May 30, 2014
79	Columbia Savings Bank	May 23, 2014
80	AztecAmerica Bank	May 16, 2014
81	Allendale County Bank	April 25, 2014
82	Vantage Point Bank	February 28, 2014
83	Syringa Bank	January 31, 2014
84	The Bank of Union	January 24, 2014
85	DuPage National Bank	January 17, 2014
86	Hometown National Bank	October 2, 2015
87	The Bank of Georgia	October 2, 2015
88	Premier Bank	July 10, 2015
89	Edgebrook Bank	May 8, 2015
90	Doral Bank	February 27, 2015
91	Capitol City Bank & Trust Company	February 13, 2015
92	Highland Community Bank	January 23, 2015
93	First National Bank of Crestview	January 16, 2015

Source: FDIC

Note: Details of the banks' failed status can be found from the official site

Annex III List of Turkish Failed Banks

Banks	Date of Transfer to SDIF	Current Status
Egebank	21-Dec-99	It was merged with Sümerbank on January 26, 2001.
Yurtbank	21-Dec-99	It was merged with Sümerbank on January 26, 2001.
Bank Kapital	27-Oct-00	It was merged with Sümerbank on January 26, 2001.
Ulusalbank	28-Feb-01	It was merged with Sümerbank on April 17, 2001.
Interbank	7-Jan-99	It was merged with Etibank on June 15, 2001.
Iktisat Bankası	15-Mar-01	Its banking license was revoked as of December 7, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 4, 2002 the liquidation decision was revoked and the Bank was merged under Bayrndirbank.
Kentbank	9-Jul-01	Its banking license was revoked as of December 28, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 4, 2002 the liquidation decision was revoked and the Bank was merged under Bayindirbank
Etibank	27-Oct-00	Its banking license was revoked as of December 28, 2001 and the liquidation process was initiated. Upon the resolution adopted in the General Assembly Meeting on April 4, 2002 the liquidation decision was revoked and the Bank was merged under Bayindirbank
EGSBank	9-Jul-01	Its banking license was revoked as of January 18, 2002 and merged with Bayindirbank as of the same date.
Toprakbank	30-Nov-01	Its banking license was revoked as of September 30, 2002 and merged with Bayindirbank on the same date.
Pamukbank	19-Jun-02	In accordance with the Act No. 5230 regarding "Transfer of Pamukbank Turk Anonim Sirketi to Türkiye Halk Bankasi Anonim Sirketi and the Act Concerning Making Changes in Some Acts" it was transferred to Türkiye Halk Bankasi A.§. on November 12, 2004.
BANKS SOLD		
Bank Ekspres	12-Dec-98	It was sold to Tekfen Group on June 30, 2001. Merger of Bank Ekspres A.S. with Tekfenbank A.S. was approved by BRSA on October 18, 2001. It carries on its activities as Tekfenbank A.S.
Demirbank	6-Dec-00	A share transfer agreement was signed with HSBC Bank Pic. On September 20, 2001 and actual share transfer was realized on October 30, 2001.

Sumerbank	21-Dec-99	Merged Sumerbank was sold to Oyak Group on August 9, 2001, the transfer of Sumerbank to Oyakbank A.S. was registered on January 11, 2002. It carries on its activities as Oyakbank A.S.
Sitebank	9-Jul-01	A share transfer agreement was signed with Novabank SA on December 20, 2001 and share transfer was realized on January 25, 2002
BANKS UNDER LIQUIDATION		
Bayindir Bank (Birlesik Fon Bankasi)	9-Jul-01	It is determined as a bridge bank to carry out the function of asset management and bank's tide designated in main contract was changed as "Birlesik Fon Bankasi A.S." in accordance with the Article No. 109 of the Banking Law No. 5411 and the Resolution No. 515 dated December 7, 2005 of the Fund Board.

Source: SDIF