Agricultural Banking and the Bank Failures of the Late 2000s Great Recession: Early Warning Signals and Technical Efficiency Analyses

by

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(Under the Direction of Cesar L. Escalante)

ABSTRACT

The late-2000s Great Recession led to a surge of bank failures in the United States with nearly three hundred banks failing from 2009 to 2010. Recalling the farm crises of the 1980s where the farm sector was pinpointed as one of the major precursors of economic turmoil, this study is an attempt to validate if the agricultural sector can once again be labeled as an instigator of such economic pandemonium using early warning models and technical efficiency analytical techniques. The empirical results indicate that exposure to agribusiness operations does not necessarily enhance a banks' tendency to fail. This lends support to the reality that agricultural loan delinquency rates are consistently below the banks' overall loan delinquency rates, thus confirming that agricultural lenders are in relatively stronger financial health. The technical efficiency analyses also confirm our contention that surviving agricultural banks are operating more efficiently than successful non-agricultural banks.

INDEX WORDS: Agricultural Banking, Early warning signals, In-sample accuracy, Out-of-sample forecasting, Stochastic Frontier Analysis, Technical efficiency

AGRICULTURAL BANKING AND THE BANK FAILURES OF THE LATE 2000S GREAT RECESSION: EARLY WARNING SIGNALS AND TECHNICAL EFFICIENCY ANALYSES

by

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DEDICATION

Dedicated to my parents, Fanying Zeng and Hong Li, and my beloved Shengfei Fu, for their love and support.

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CHAPTER I

INTRODUCTION

"When written in Chinese, the word " 危机（crisis）" is composed of two characters - one represents danger and the other represents opportunity."
*~ **John F. Kennedy**, address, 12 April 1959*

1.1The Great Recession of the Late 2000s

The global economy experienced a general slowdown in economic activity in the late 2000s that economists and business analysts consider as the worst economic crises experienced since World War II and the longest downturn since the 1930s Great Depression. Dubbed as the Great Recession (Wessel, 2010), worsening global economic conditions began in December 2007 as declared by the National Bureau of Economic Research (NBER) that took cues from the deteriorating conditions in the labor market (Isidore, 2008).

The United States economy was not spared from the global crises. In the local economy, the period of the late 2000s was marked by trends of high unemployment, declining real estate values, bankruptcies and foreclosures, among many other indicators (Rutenber and Thee-Brenan, 2011). A widely accepted theory of the real culprit that significantly launched the onset of the economic crises in the United States was the breakdown of the real estate industry (Isidore, 2008). The housing downturn started in 2006 when housing process dropped significantly after reaching peak levels in the early 2000s. This resulted in an abrupt increase in loan defaults and mortgage foreclosures that led to widespread crises in the banking industry.

1.2 Banking Crises

The late-2000s financial crisis led to a surge of bank failures in the United States at an overwhelming rate not observed in many years. The cycle of seizures started in 2007, and by the end of 2010, a total of 325 banks had failed. In contrast, only 24 banks had failed in the seven-year period prior to 2007. California, Florida, Georgia, and Illinois were among the states hardest hit by bank shutdowns, with 34, 45, 52, 38 failed banks, respectively, since 2007. Figure 1.1 shows the state-level concentration of U.S. bank failures that occurred just in the two-year period from 2009 to 2010.

Faced with a looming crisis in early 2008, the Federal Deposit Insurance Corporation (FDIC) brought officials - who had served during a wave of bank failures in the savings-and-loan crisis - out of retirement (Luke Mullins, 2008). The move came a week after Comptroller of the Currency, John Dugan, predicted "an increase in bank failures" in the coming months. At that time, experts expressed concerns only with certain smaller banks that concentrated in real estate lending, while the giant banks were considered to face less danger. However, more and more large banks failed as time went by.

The failure of Washington Mutual in September 2008 was the largest in U.S. banking history. Banks with over a billion dollars in assets at the time of failure, such as IndyMac, Colonial Bank, and Guaranty bank, were also taken over by the FDIC from 2008 to 2010.

The FDIC's 2010 loss estimate for bank failures rose to $24.18 billion at year's end which

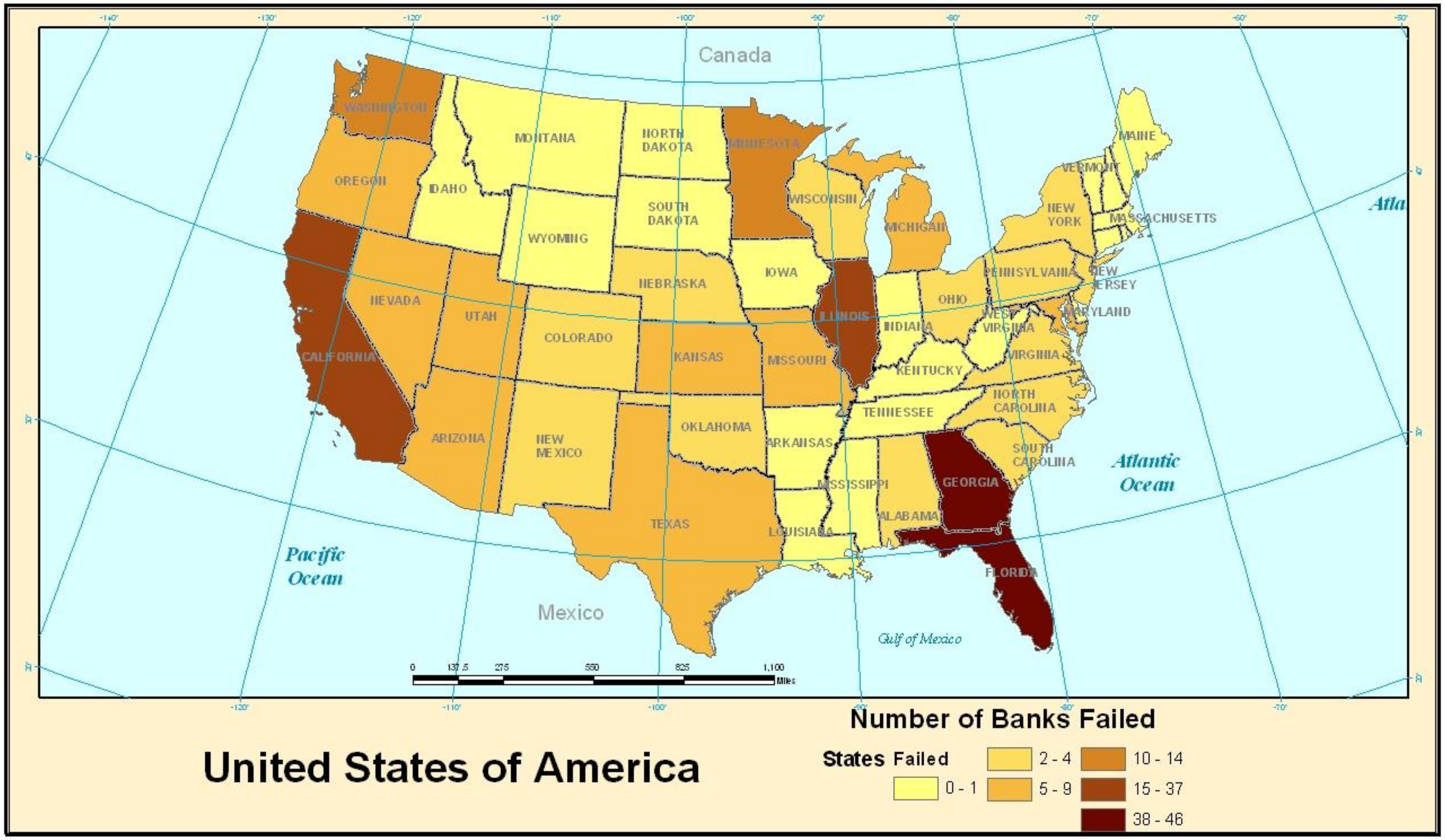

Figure1.1: Concentration of Bank Failures across all U.S. States: 2009-2010

was higher than its forecasted loss estimate of $22.17 billion. The bankruptcy of banks created a loss of $3.31 billion for the regulator's deposit insurance fund. The FDIC projects the cost of bank failures to total around $60 billion from 2010 through 2014. In addition, banks have been asked to pay an additional $45 billion premium for 2010 through 2012 to replenish the insurance fund (Marcy Gordon, 2010).

Even with the declaration of the National Bureau of Economic Research that the country's longest recessionary period had ended in June 2009 (Escalante, 2010), small and regional banks continued to bear the brunt of the recession where many companies shut down, vacating shopping malls and office buildings financed by the loans (Marcy Gordon.2010). The FDIC continued to keep on its watch list some 829 banks that are considered as problem banks (O'Boyle, 2010). Such banks have not yet declared bankrupt and not identified publicly, but are monitored nonetheless due to certain indicators of operating and financial conditions that suggest potential threats to business viability and survival. Notably, in 2006 prior to the recession, there were only 50 banks on the FDIC watch list.

Subprime residential mortgages crisis, one of the first indicators of the late-2000s financial crisis, was considered to have delivered the coup de grace to the country's banking system and consequently led to the wave of bank failures since 2007. The subprime mortgage is viewed as riskier than a regular loan because its expected probability of default is higher (Demyanyk and Hasan, 2010). Speculative borrowing in residential real estate has been pinpointed as a contributing factor to the subprime mortgage crisis. A lower interest rate and large inflows of foreign funds created an easy credit condition and fuelled the housing market boom with real estate prices dramatically increasing since 2002. However, the housing bubble burst after the housing prices peaked in early 2006 and started to drop in late 2006 and 2007. High inflation and tight financial market conditions caused the default by hundreds of thousands of borrowers within a short period in the subprime lending market, and resulted in a number of major U.S. subprime lending institutions closing their businesses. Meanwhile, the bad residential real estate loans, including the subprime mortgages, hit the bank industry hardly that FDIC started to shut down bad banks at a faster rate. Following 25 bank closures in 2008, a total of 140 banks were seized in 2009. The rate of bank bankruptcy even increased in 2010, with 157 bank failures, the highest level since 1992 when the savings-and-loan crisis broke out.

It is said that the problems plaguing the bank industry have migrated from subprime residential mortgages to commercial real estate, especially for those community banks with higher concentrations of loan exposure to this industry (Daly, 2010). In April 2011, the delinquency rate on commercial mortgage-backed securities hit a record 9.62%, accompanied by the failure of 13 banks that were heavily exposed to commercial real estate in the same month, the highest monthly total since July 2010 (Sweet, 2011).

1.3 Agricultural Lending under the Recession

In times of economic hardships, there is often less confidence in the resilience and endurance of the agricultural sector in weathering business survival challenges. The farm sector is naturally too vulnerable to business and financial risks. The operating conditions of farm businesses usually subject them to unique sources of risk and uncertainty often not faced by other industries (such as weather, pests, diseases and other factors affecting productivity, marketing and other facets of production).

Such perceptions of the potential business vulnerability of farm businesses are often translated to high credit risks, if not indifference by lenders to farm borrowers. As banking failures plagued the financial industry during the late 2000s recession, some experts suspect that significant loan exposures to agricultural activities could increase the probability of bank failure.

Such paranoia has some historical basis. Still fresh among many people is the memory of the farm crisis back in 1980s, during which more than 1,600 banks closed due to the large amount of delinquent farm loans caused by farm operating losses and a fall in agricultural land values.

Although during the recent crises only 12 agricultural banks out of total 325 bankrupt commercial banks have failed, the increasing trend in bank bankruptcies still continues to raise some concern on the possible breakdown of some agricultural banks (Agricultural Finance Databook, 2010). Daniel Rozycki, associate economist of Federal Reserve Bank of Minneapolis, actually sees some similarities of the late 2000s recession to the 1980s farm crisis in recent agricultural sector trends, such as the prices of some key crops that had doubled or tripled from 2006 to 2008 and have been falling sharply since then, and that farmland price has began to recede after reaching record high levels in 2008. The speculation is that if land and crop prices continue to fall, the agricultural banks' operational viability will be threatened.

Meanwhile, evidence shows some modifications in agricultural lending activities during the recession. In general, bankers have always been cautious in their dealings with farm borrowers, and they tend to ascribe higher credit risk ratings to farm borrowers vis-à-vis other borrowers. Facing decreased production prices and increased input prices, farmers find themselves in a situation where more and more banks were reluctant to provide financing (Bill Jackson, 2009). The failure of New Frontier Bank in Greeley, Colorado has worsened the situation and sent many of the farms into a tailspin (Kirk Siegler, 2009). New Frontier was the biggest agricultural bank that failed in 2009 with $800 million out of its $2 billion assets locked in massive agricultural loans, and FDIC had to intervene and pay more than $35 million to keep farms open.

1.4 The True State of the Farm Economy under the Recession

The true state of the agricultural industry during the recessionary times actually tells a slightly different story. In the lending side, Ellinger and Sherrick (2010) claimed that the agricultural lenders are actually generally in strong financial health because most of the agricultural-related institutions did not lend heavily to the real estate industry, and agricultural banks did not invest in the structured securities that have lost substantial market value.

These assertions are supported by data provided in the Agricultural Finance Data book compiled and released by the Federal Reserve Board. In its reports, the relative financial strength of agricultural banks in the industry is evident in their improving liquidity conditions. The Federal Reserve Bank of Atlanta, for instance, reports that agricultural banks in its region (including Georgia and other southeastern states) have posted improvements in their loan-deposit ratios that dropped from 0.84 in 2008 to 0.78 as of early 2010, which is now almost at its pre-recession level. Moreover, as the banking industry experienced significant increases in overall loan delinquency rates from 1.73% (1st quarter 2007) to 7.36% (1st quarter 2010), the comparable delinquency rates of the banks' agricultural loan portfolios posted very modest increases – from 1.18% to just 2.89% during the same period. The agricultural loan delinquency rates have consistently been below the banks' overall loan delinquency rates since the 1st quarter of 2004 (see Figure 1.2). The gap between overall and agricultural loan delinquency rates has widened since then.

In the same report, it has been evident that national farm bankruptcy trends comprise a very small portion of aggregate business and non-business bankruptcy filings recorded in the past several years. Specifically, Chapter 12 (farm-related) bankruptcies grew from 376 in 2007 to 544 in 2009. These figures comprise 0.044% and 0.037%, respectively, of total filings in all states. In Georgia, only 10 farms filed bankruptcy in 2007 and another 43 filed in 2009. As of the first quarter of 2010, 9 Georgia farms have thus far closed their businesses.

Another report published by the Economic Research Service of the United States Department of Agriculture (ERS-USDA) indicates that the farm sector has consistently maintained growth rates in farm assets and equity that far exceed the growth in farm debt (Figure 1.3). In more than two decades, both the rate of increase and the absolute increase in asset values have significantly exceeded those of farm debt. It is worth noting that from a debt-to-asset ratio of 22.19 in 1985, the farm sector has managed to bring that ratio down to 11.33 in 2009 (Figure 1.4) – which actually has improved further to 10.74 in 2010. Since the 1980s, the farm sector's debt repayment capacity utilization (DRCU), which accounts for all debt obligations and compares them with maximum debt repayment capabilities, has improved tremendously.

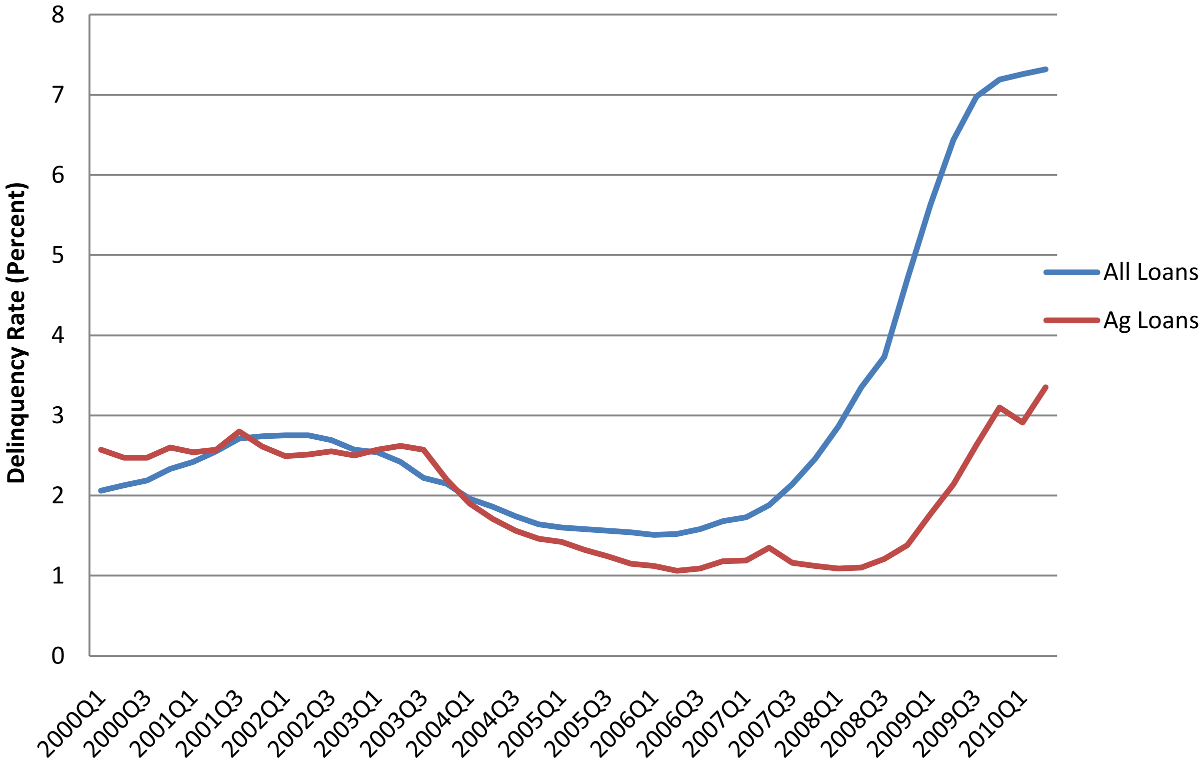

Figure 1.2: National Loan Delinquency Rates, Quarterly, 2000-2010

Source: Federal Reserve Board

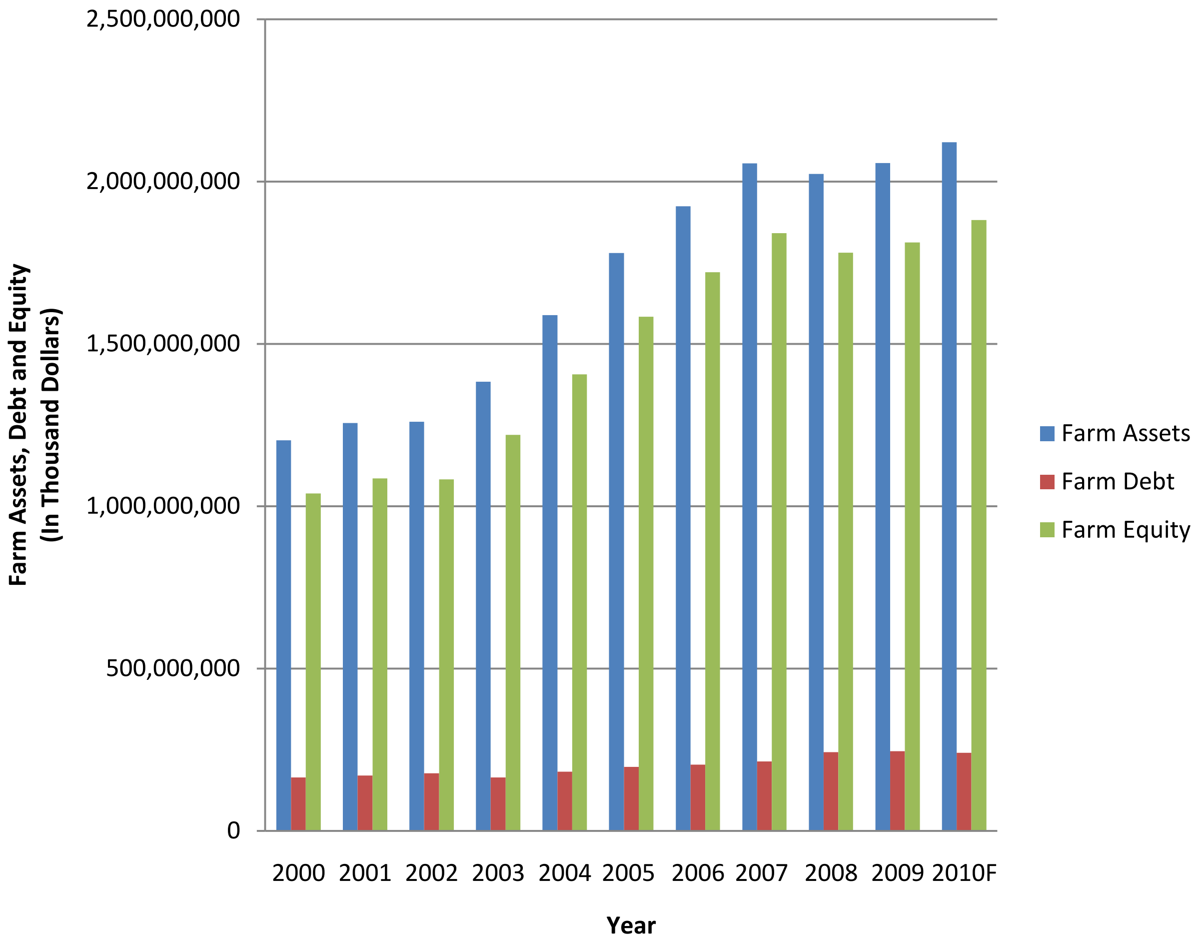

Figure 1.3: Total Assets, Debt, and Equity of U.S. Farms, 2000-2010

Source: Economic Research Service, USDA

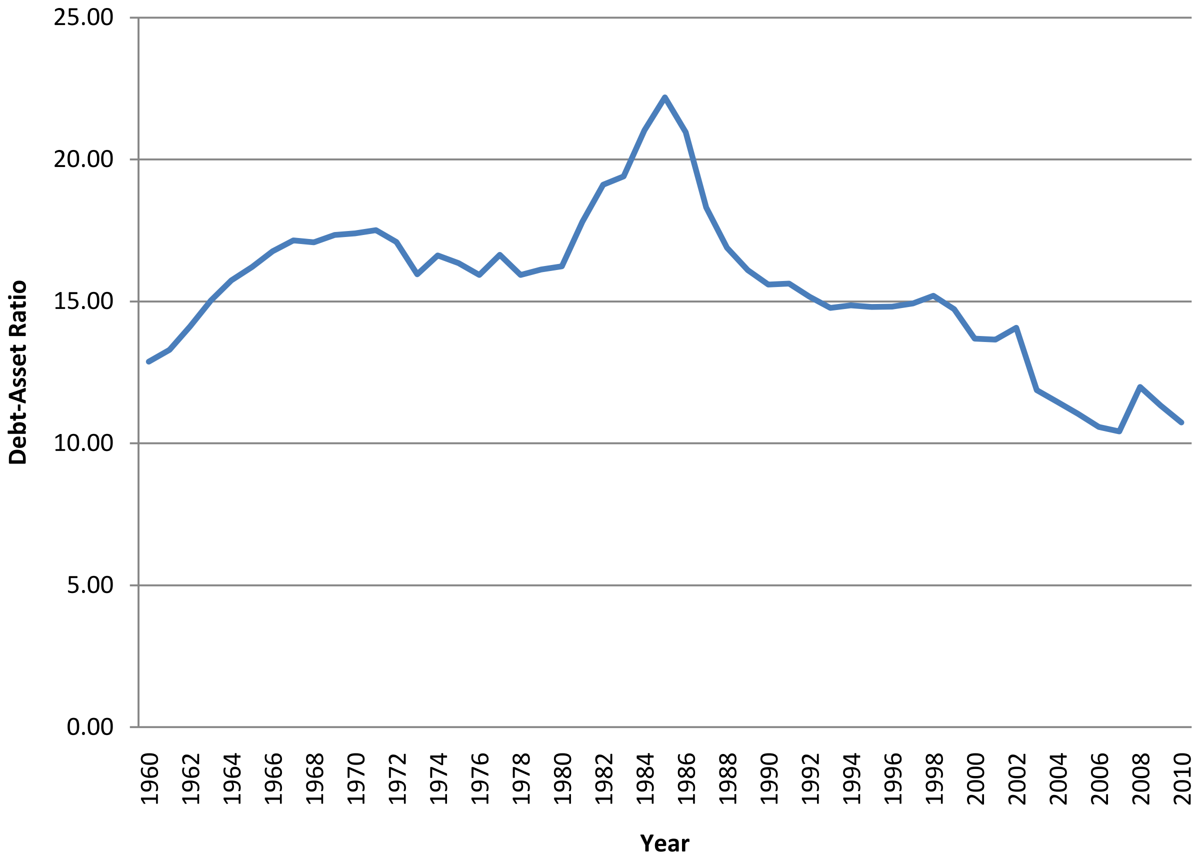

Figure 1.4: Debt-Asset Ratio of U.S. Farms, 1960-2010

Source: Economic Research Service, USDA

1.5 Research Objectives

In the face of the current recession which has especially manifested itself in the financial industry, it is important to probe more deeply and understand the causes of bank failures, which should hopefully provide insights on more effective solutions to the current crises or cautionary policies that will prevent its duplication in the future. If we can detect early warning signals of a bank's tendency to eventually fail, then operating decisions and strategies can be modified and realigned to address these factors and help a bank avoid failure in the future.

Many previous studies have examined the determinants of bank failures from previous episodes of financial crises by analyzing the nature and consequences of management decisions, testing scale and scope efficiency, investigating the effect of insider loans, and introducing different capital ratios as predictors of bank performance. Some researchers focused on developing different bankruptcy prediction models, such as the basic probit/logit model or hazard model allowing for time-varying firm-specific characteristics and macroeconomic dependencies.

This study differentiates itself from previous empirical works by its special focus on the role of the agricultural finance industry in the ensuing credit crises. This study will reconcile the contrasting attitudes towards the farm sector's role or influence in the ensuing economic crises. Specifically, this research will address the issue of whether or not agriculture, which is more vulnerable to a wider range of risk and uncertainty factors, has significantly influenced the incidence or probability of banking failures during the current recessionary period.

Moreover, this study adopts a more comprehensive approach in understanding bank failures by a retrospective approach to bank failure prediction involving several time period models. The empirical analyses are also enriched by the introduction of the technical efficiency model and its determinants. The technical efficiency analytical framework will also allow the comparative evaluation of internal and external factors that could affect a bank's probability of failure.

Specifically, this study will address the following objectives:

1. To determine the factors that significantly caused bank failures, with special attention given to the role of the agricultural lending portfolios of commercial banks;
2. To determine the length of time prior to the actual bank bankruptcy declarations that early warning signals among the banks' operating and lending decisions, in addition to certain macroeconomic indicators, could be detected;
3. To further analyze bank failures from the technical efficiency standpoint under a stochastic cost frontier framework and evaluate the reliability of the technical efficiency measure (vis-à-vis external, macroeconomic factors) as a determinant of the banks' financial health and probability to succeed or fail at the height of the current recessionary period.

The 1st objective will be addressed through a bank failure regression model employing logit estimation techniques. Several cross-sectional datasets for commercial banks will be developed from the Banking Call Report database available from the Chicago Federal Reserve Board's website. These datasets will include information on the operating and lending decisions of both banks that failed and survived the current economic crises. The banking datasets are also supplemented by macroeconomic indicator variables, compiled at the state level, to determine whether the banks' internal decisions are enhanced or adversely affected by prevailing industry or economic operating environments.

The 2nd objective will be addressed by constructing several cross-sectional datasets, starting from an initial period of six months from actual bank failure, and re-tracking backwards in six-month period increments until 4 years (48 months) prior to the bankruptcy declaration. These models will analyze trends in the significance of probable bank failure determinants over time prior to bankruptcy. In other words, this analysis will determine how far back in time could the early warning signals of bank failure be detected. Throughout this analysis, the special focus of this research on agricultural credit issues will be maintained as its impact or significance in the models will be analyzed vis-à-vis the other bank failure indicators. The different period models' predictive powers will be determined through post-estimation procedures such as in-sample and out-of sample prediction techniques.

In addressing the 3rd objective, a technical efficiency model based on the stochastic cost frontier framework is developed. A technical efficiency score for each bank (both failed and surviving entities) will be calculated using a set of operational input and output variables estimated under the stochastic cost frontier approach. Instrumental variable estimation using the Probit approach (IV Probit) will be employed in a dataset compiled using the two most recent years in the dataset, 2009 and 2010. In this model, the calculated technical efficiency scores are endogenously determined by an array of instrumental variables that include the bank performance factors considered in the bank failure prediction models. The IV Probit model will then evaluate the relative performance of the TE variable, which now becomes a collective measure of overall bank financial performance, vis-à-vis variables that capture the prevailing macroeconomic conditions. The results of this analysis will supplement and enhance the findings of the bank failure prediction models in the first two objectives.

1.6 Thesis Organization

This thesis manuscript is divided into six chapters, which are discussed in detail below:

Chapter 1 provides the background of this study and outlines the objectives of the thesis. This chapter introduces the late 2000s financial crisis and its relations with the wave of bank failures from 2007 to 2010. Possible factors that caused bank failure, such as the subprime residential mortgage and commercial real estate, are introduced. Contrasting viewpoints on the role of agricultural lending in the ensuing financial crises are provided in this chapter.

Chapter 2 reviews the related studies on bank failure. This chapter is divided into four sections. The first section reviews earlier studies on bank failure and its determinants. The second section briefly summarizes some early warning models used in empirical studies. The third section is devoted to a review of bank efficiency literature. The fourth section summarizes some studies about agricultural bank efficiency and determinants of agricultural bank failure.

Chapter 3 introduces the methodology used in this study, briefly describes the concepts of logit regression, marginal effect and the stochastic frontier framework used in the efficiency analysis.

Chapter 4 describes the data source, identifies relevant banks variables and state specific variables and provides justifications for the choice of these variables included in this study's empirical models.

Chapter 5 presents the results from the bank failure prediction models and the technical efficiency analysis. The significance of the results of the bank failure prediction models is discussed, along with the results of in-sample and out-of-sample forecasting to determine the models' relevance and predictive efficiency. The technical efficiency scores are then presented in a comparative summary presentation. This discussion is then followed by a discussion of the IV Probit model results.

Finally, Chapter 6 summarizes the results of this research, presents its conclusions and discusses further research implications.

CHAPTER II

REVIEW OF LITERATURE

This chapter presents a review of previous empirical works under four general themes. The first section presents studies that dealt with the determinants of bank failures identified among key bank operating and structural variables. The second section summarizes the results of empirical investigations on early bank failure warning models. The third section presents important links between bank failure and efficiency analysis. The final section discusses the performance of agricultural banks as analyzed under efficiency models.

2.1 Analyses of Bank Failure Determinants and Prediction

Bank failures have been analyzed quite extensively in the corporate finance literature. In the 1980s, bank failures reached record post-Depression rates and more than 200 banks closed each year from 1987 through 1989. Thomson(1991) used 1983-1988 book data from the June and December Federal Financial Institutions Examination Council's Reports of Condition and Income (Call Report) to analyze factors causing bank failure. A novel element of his model is the incorporation of measurements of local economic conditions, along with traditional balance-sheet and income-statement measures of risks, in the probable menu of factors that would influence the likelihood of bank failure. He also tried to develop the ability to differentiate between well-behaved banks and troubled banks in order to prevent a bank from failing or minimize the cost of bank failures. His study concludes that the majorities of CAMEL[1]-motivated proxy variables, as well as the economic conditions in the market area, were significantly related to the probability of bank failure as early as four years before the failure.

Wheelock and Wilson (2000) tried to identify bank characteristics that make individual U.S. banks more likely to fail or be acquired. They used competing-risks hazard model based on CAMEL related bank variables, and found that "highly leveraged banks, banks with low earnings, low liquidity, or risky asset portfolios are more likely to fail than other banks." (Wheelock and Wilson, 2000, PP.128) Their study further concludes that geographic diversification can limit failures when statewide branching is allowed, and that management inefficiency can increase the likelihood of the bank failure significantly.

Exploring why some agricultural banks failed while others remained profitable, Belongia and Gilbert (1990) analyzed bank failures by looking into the effects of portfolio decisions by bank managers. In order to isolate the effects of portfolio decisions, they excluded variables that reflect local economic conditions or are correlated with the variables under the control of bank management. Balance sheet items under management control were treated as independent variables in the probit model. These factors were found to affect the probability of bank failures significantly.

Lawrence, Kummer and Arshadi (1987) was presumably the first empirical work that developed linkages between the incidence of insider loan transactions to bank failures. They identified 31 out of the 1,171 failed banks that had insider borrowing exceeding 25% of their

[1] CAMEL: Capital adequacy, Asset quality, Management, Earnings, Liquidity.

equity base in 1986. Their study's findings, even though not too strongly conclusive enough, led them to suspect that insider loans might have exacerbated the already worsening conditions of banks that eventually led them to bankruptcy. Following such line of argument, several studies subsequently introduced insider loan as a probable bank failure determinant into their models(Graham and Horner, 1988, Seballos and Thomson,1990, Belongia and Gilbert,1990, Thomson, 1991). Thomson (1991) and Graham and Horner (1988) conceded that banks with higher percentage of loan to insiders tend to have higher probability of failure rates. The findings of Seballos and Thomson (1990) even asserted that failed banks made an average of three times as many loans to insiders as did those in the non-failed sample. Their study's sample covered successful and failed banks during the 1980s financial crises.

In addition to the insider loan factor, other studies also considered overhead cost as a strong indicator to analyze bank failure and bank efficiency(Demirguc-Kunt, et al., 2003, Seballos and Thomson, 1990, Thomson, 1991). Overhead cost refers to an ongoing expense of operating banks. As a measure of operating efficiency, high overhead costs may indicate bank inefficiencies.

Estrella, Park and Peristiani (2000) focused on using three types of capital ratios – risk-weighted ratio, leverage ratio, and gross revenue ratios – to predict the bank failure. The capital ratio is calculated by dividing a bank's absolute amount of capital by the proxy for its absolute level of risk. It is a good indicator to gauge the absolute risk, as it takes absolute capital amount into account. The simple ratios, leverage ratio and gross revenue ratio as well as the complex risk-weighted ratio can be used as indicators of solvency over one- or two-year horizons. Risk-weighted ratios, however, are considered to be better representations of solvency over longer horizons.

A number of studies analyzed the effect of product diversification or level of industry concentration on bank performance. These studies usually adopted the Herfindahl index approach, which is a measurement of bank level concentration widely used by regulators in the bank industry analysis. Thomson (1991) incorporated in his model the Herfindahl index as a measurement of the diversification of the risky asset and used it as a proxy for portfolio risk, by taking sum of the squares of different loan ratios. Deyoung and Hasan (DeYoung and Hasan, 1998) used the Herfindahl index as a proxy for the degree of competitive rivalry for those banks headquartered in Metropolitan Statistical Areas. The index was found to have a positive relationship with profit efficiency under the assumption that concentration leads to higher prices and profits in their study.

Duration gap analysis is used in the bank industry to measure interest-rate risk. It examines the sensitivity of the market value of the financial institution's net worth to changes in interest rates(Mishkin, 2007). Kaufman(1984) measured the interest rate risk by taking the difference of the institution's average asset durations and its average deposit durations. Belongia and Gilbert (1990) applied this duration gap analysis to the study of bank failures. They concluded that the bank would be vulnerable to large losses under two scenarios: 1) when both long-term and short-term interest rates rose; and 2) the long-term rates remained unchanged while the short-term interest rates rose.

2.2 Early Bank Failure Warning Models

In order to predict which institutions are most likely to be at risk and warn interested parties of their potential failure, various researchers have been using multivariate techniques to devise an early-warning model. Among the earlier studies, Beaver (1966) conducted an univariate analysis (one ratio at a time) by examining the predictive ability of financial ratios with respect to bankruptcy. Altman (1977) pursued this line of research and expanded the study to a multivariate analysis. He first used discriminate analysis for predicting bankruptcy of nonfinancial firms and then applied such analytical framework to construct and evaluate a performance predictor system for detecting serious problems of Savings & Loans Associations. The work of Beaver and Altman initiated the assessment of the predictability of bank failure(van der Ploeg, 2010). Meyer and Pifer (1970) pioneered the application of early warning analysis on banks. They used stepwise regression program with binary dependent dummy variables to discriminate between bankrupt and solvent banks that faced similar local and national market conditions.

Several studies applied either the probit or logit model to publicly available financial data to predict bank failures(Cole and Gunther, 1998, Hanweck, 1977, Martin, 1977, Pantalone and Platt, 1987, Thomson, 1991). What these studies have in common is that they divided the banks into failure and non-failure groups and treated the classification as binary dependent variable regressed against a host of explanatory variables that could influence a bank’s probability of failure. Thomson (1991) used logit regression with a binary dependent variable, with 1 for a failed bank and 0 otherwise. He suggested that the logit model is preferred to the probit because logit is not sensitive to the uneven sampling frequency problem.

Another widely used model is the hazard model, developed by Cox in his study “Regression Models and Life-Tables” of a biomedical framework(Cox, 1972). Lane, et al. (1986) first applied the Cox proportional hazard model to the prediction of bank failure. An advantage the hazard model has over the logit/probit is that it models the expected time to failure, instead of only setting a binary dependent variable indicating failure or non-failure. Wheelock and Wilson (2000) used the Cox proportional hazard models with time-varying covariates to examine the predictive ability of the model as well as to determine the factors that contribute to the bank failure and acquisitions.

Barr and Siems (1997) ventured into the application of the data envelopment analysis (DEA) efficiency variable to measure the management quality. They presented a new approach to predicting bank failures that can detect the initial aggravation of a bank’s financial conditions up to two years prior to insolvency. The models used proxies for CAMEL rating and a variable that capture the local economic conditions. The results emphasize the idea that management-related factors are crucial to the successful operation of a bank.

Neutral Networks (NN) model is developed from the field of artificial intelligence, and it uses nonlinear function approximation tools that may test the relationship between independent variables and dependent variable (Demyanyk and Hasan, 2010).Tam and Kiang pioneered the application of the NN model to the prediction of bank failure(Tam and Kiang, 1990, Tam and Kiang, 1992). They compared the approach with other methods such as linear classifier and logistic regression techniques. The empirical results show that NN is a promising method of evaluating bank conditions in terms of predictive accuracy, adaptability, and robustness. However, possibility of over-fitting the network, inefficient computation, and difficulty in explaining the effect of individual inputs could bring some limitations.

2.3 Bank Efficiency Analysis

Inefficient bank decisions and operations will increase a bank's operating costs and increase the risk of failure. Facing an increasingly competitive environment and realizing the importance of efficiency analysis, the bank industry has conducted a variety of efficiency analyses. Empirical studies have examined many issues related to the operations of financial institutions, such as economies of scale and scope, technical inefficiency and allocative inefficiency, the efficiency implications of bank mergers and branch banking, and productivity change.

Technical efficiency measures the ability of a firm to produce optimal output from a given set of inputs (Farrell, 1957). Allocative efficiency measures the ability of a firm to use the inputs in optimal proportions and quantities to achieve the minimum costs, at a price level equals to the marginal cost of production.

A common approach to examine bank efficiency is to utilize frontier cost function. One of its sub-areas, the parametric frontier model, maximizes possible output, which is assumed to be a function of certain inputs. Based on this model, Aigner (1976) introduced a stochastic component into the production frontier model in developing an efficiency analytical framework. This Stochastic Frontier Analysis (SFA) is one of the most widely used methods applied to the parametric approach. A functional form and two part error terms have been used in the stochastic frontier approach. The Maximum Likelihood (ML) estimation or corrected ordinary least squares is used to estimate the frontier given appropriate distributional assumptions for the error components(Färe, et al., 1985). Elyasiani and Mehdian (1990) also specified a production frontier for bank in their study and evaluate the bank performance based on banks' measured deviation between actual output and potential output. Several studies used the stochastic parametric cost frontier, which models the bank cost structure using a translog cost function form (Ellinger and Neff, 1993, Neff, et al., 1994). The translog cost function has been used extensively in banking cost studies for its flexible functional form which contains both the Cobb-Douglas and Constant Elasticity of Substitution (CES) as special cases (Ellinger and Neff, 1993).

As an alternative to the parametric approach, a study used a nonparametric frontier approach to calculate the overall, technical, allocative, and scale efficiencies for hundreds of banks (Aly, et al., 1990). In the nonparametric approach, linear programming is used to construct a piecewise-linear, best-practice frontier for each bank. The nonparametric approach avoids the need to specify a particular functional form of the bank cost relationship. In addition, the nonparametric approach is deterministic, for all deviations from the frontier are interpreted as inefficiencies.

Other researchers also used profit functions. Neff, Dixon, and Shu (1994) estimated profit functions using the Fuss normalized quadratic functional form, which treats normalized profit variable as function of some specified outputs, inputs, and fixed netputs (transaction deposits and physical capital). The constructed system was estimated using non-linear Seemingly Unrelated Regression, which is also used by Berger, Hancock and Humphrey (1993).

2.4 Agricultural Bank Failures and Efficiency Analysis

Majority of bank studies have been primarily focused on commercial banks, with only a few empirical works that have taken interest in the analysis of agricultural banks and their efficiency. The agricultural banks, by the FDIC criterion, are those financial institutions whose agricultural loan to total loan ratio is at least 25% and therefore represent a focused set of banks supporting agricultural activities. The bank can limit their chances of failure by diversifying their loan portfolios into different categories. However, agricultural banks are criticized for their limited portfolio diversification opportunities, and are perceived or expected to more likely fail when the economy experiences a slowdown in activity, such as the ensuing economic recession of the late 2000s. With such perception of the alleged vulnerability of agricultural banks to economic downturns, Kilesen and Gilbert (1996) offered some suggestions in their article for bank survival. For instance, small agricultural banks are advised to merge with large banking organizations, while those banks with the highest percentages of their assets invested in agricultural loans should maintain a higher ratio of equity to total assets (Kliesen and Gilbert, 1996).

Ellinger and Neff (1993) discussed the major issues associated with efficiency measurement of financial institutions and evaluated the efficiency of a sample of agricultural banks by comparing the Stochastic Cost Frontier and the Nonparametric Cost Frontier models, which are the two most commonly used methods in the efficiency analysis of commercial banks.

Their results indicate that each model or empirical approach has distinct advantages and disadvantages. Compared to the nonparametric models, which usually result in larger and more disperse measures of bank inefficiency, stochastic models are more applicable to the efficiency measurement of agricultural banks with the use of Call Report data.

Neff, Dixon, and Zhu (1994) have presented one the earlier empirical works on agricultural banks' efficiency. They compared the efficiency analysis methods such as nonparametric, stochastic parametric and thick frontier methods, and used stochastic parametric cost frontier and profit model to estimate the efficiencies. They found bank size to be strongly and negatively related to profit inefficiency while agricultural loan ratio is positively related to profit inefficiency. However, the latter results are questionable because larger banks have smaller agricultural loan-to-deposit ratios(Neff, et al., 1994).

Another study measured economies of scale and scope in agricultural banking (Featherstone and Moss, 1994). Instead of using the normal translog cost function in multiproduct cost analysis, they used a normalized quadratic translog functional form to avoid the possibility of having the translog specification producing a poor approximation when applied to all bank sizes. Their results indicate that, regardless of whether curvature was or was not imposed in the function, economies of diversification are not realized when agricultural lending is combined into an institution that has not been previously engaged in agricultural lending.

A doctoral dissertation at the Department of Agricultural and Applied Economics of the University of Georgia (Yu, 2009) looked into the effect of bank specialization (with banks being classified as agricultural and non-agricultural banks) and size categories on various measures of efficiency. A stochastic input distance function was used in his study to compute the technical efficiency and allocative efficiency. His research produced results that emphasize certain advantages of the agricultural banks' structural and operating characteristics. His findings clarify those decisions of agricultural banks to adjust labors and capitals proved to be more efficiency-enhancing decisions than those implemented by non-agricultural banks. Moreover, his study also contends that agricultural banks are more technically efficient than non-agricultural banks.

In the face of the recent economic pandemonium and the consequent crises in the financial industry, Ellinger and Sherrick(2010) embarked on a study that produced results suggesting that agricultural lenders are generally in strong financial health because most of the agricultural-related institutions did not participate in the housing lending procedures, and agricultural banks did not invest in the structured securities that have lost substantial market value. They observed that the general health of commercial banks that lend to agriculture remains strong, as only 13 of the total 6071 banks were classified as undercapitalized by FDIC.

Chapter III

METHODOLOGY

This section introduces the models used in this research. As stated in Chapter 1, this study will use bank failure prediction models to identify the significant determinants of bank failure at different time periods preceding the actual incidence of bank bankruptcy. The latter part of this thesis will use the technical efficiency model to further analyze the bank survival paradigm. The following sections will introduce and lay out the foundations of these theoretical approaches.

3.1 Determining Bank Insolvency

Although this study does not analyze the banks' financial performance conditions to identify insolvent banks (and instead uses publicly available press releases on the identification of the failed banks as well as these banks' automatic exits from the FRB call report database at the quarter following their declaration of insolvency), it is still important and necessary to understand how bank insolvency is determined.

The Federal Deposit Insurance Corporation (FDIC) is responsible for monitoring its member banks' financial performance conditions and identifying problematic and insolvent banks. As FDIC's name suggests, this institution provides insurance against loss of deposits in its member banks. The current insurance ceiling FDIC provides is $250,000 per depositor in each member bank (FDIC, FDIC Insurance Coverage Basics.).

However, in order for FDIC to continue extending such savings guarantee or insurance, its member banks have to maintain certain liquidity and reserve requirements. FDIC primarily assesses the bank's continued solvency using the risk-based capital ratio (which shall be defined in the next chapter as this is one of the variables in the empirical models) (FDIC, *FDIC Law, Regulations, Related Acts*). When a bank's risk-based capital ratio drops below 8%, it is classified by FDIC as "undercapitalized" and is then given a warning by the FDIC. If that capital ratio further deteriorates and drops below 6%, the bank is classified by FDIC as "significantly undercapitalized." Under such conditions, the FDIC can demand a change in the bank's management and pressure the bank to implement remedial or corrective actions. When that capital ratio falls to less than 2%, FDIC then classifies the bank as "critically undercapitalized." When this happens, FDIC declares the bank as insolvent and will take over management of the bank.

This study subscribes to the FDIC definition of bank insolvency. The analyses in this research use the FDIC's criterion that equates insolvency with failure. Thus, the banks categorized as failed banks in this study are those considered by FDIC as severely insolvent or "critically undercapitalized."

3.2 Empirical Design for Bank Failure Analysis

The basic framework of the models used in this study is based on traditional bank failure prediction models presented in the corporate finance literature. Typically, the prediction model is a single equation model, with the primary goal of predicting bank failures.

This study presents a variant of the typical model presented in literature differentiated through two model extensions: a) the addition of state-level variables that capture macroeconomic factors, in addition to bank performance variables; and b) the use of different time period versions of the cross-sectional model to determine earliest possible warning signals of bank failures.

The typical single-equation bank failure prediction model employs qualitative regression techniques. Qualitative response (QR) models are referred to as the estimation of relationships involving dependent variables that are non-continuous or qualitative in nature. Probit and logit models are among the most commonly used QR approaches in marketing applications. Although it is said that the choice between probit and logit model is largely a matter of personal preference rather than practical significant, some studies suggest that when faced with uneven sampling frequency problem, logit is more appropriate than probit (Maddala, 1983, Thomson, 1991). Martin also suggests using logit model instead of probit model because of the computational difficulties (Martin, 1977). He suggests that in many practical applications, it is desirable to use an approximation to the normal distribution rather than the normal itself, and logistic distribution is a good approximation.

In the construction of the logit model, we assume the probability of bank failure y_i^* be defined as a linear function of a vector of covariates x_i and a vector of regression coefficients β.

$$y_i^* = x_i'\beta + u_i \qquad (1)$$

where u_i stands for the error term .

In practice, y_i^* is unobservable, but we do observe

$$y_i = 1 \text{ if } y_i^* > 0$$

$$y_i = 0 \text{ if } y_i^* \leq 0 \tag{2}$$

Given the latent variable models (1) and (2), we have

$$P(y_i = 1|x) = P(y_i^* > 0|x) = P\big(u > -x_i'\beta \,\big|x\big) = 1 - F\big(-x_i'\beta\big) = F(x_i'\beta)$$

where F(·) is the cumulative distribution function for u. This yields the logit model if u is logistically distributed. The likelihood function is

$$L = \prod\nolimits_{y=0} F\big(-x_i'\beta\big) \prod\nolimits_{y=1} [1 - F\big(-x_i'\beta\big)]$$

In this case, if the cumulative distribution of u_i is the logistic, the logit model can be specified as

$$F\big(x_i'\beta\big) = \frac{\exp{(x_i'\beta)}}{1 + \exp{(x_i'\beta)}} = \frac{1}{1 + \exp{(-x_i'\beta)}}$$

However, the inference from the logit model is not straight forward, as the estimated coefficients reveal the direction of an effect but not its magnitude. In order to interpret the coefficients of the logit model, we need to estimate the marginal effect. The marginal effect for logit model is defined as

$$\frac{\partial p}{\partial x_i} = F\big(x_i'\beta\big)\{1 - F\big(x_i'\beta\big)\}\beta_j$$

There are three variants of marginal effects, average marginal effect (AME), marginal effect at a representative value (MER), and marginal effects at the mean (Cameron and Trivedi, 2009). The marginal effect at a representative value is the default mean value in STATA and is a most commonly used method. However, AME is a more appropriate method for providing a realistic interpretation of estimation results, since marginal effects at the mean is not a good approximator if some of the parameter estimates are large , as Bartus suggested(2005).

3.2.1 The Estimation Models

In order to determine the probability of failure in the bank failure prediction models, a logistic function specified as:

$$F(\,PROB_{it}) = \frac{\exp\,(\,PROB_{it})}{1+\exp\,(\,PROB_{it})} = \frac{\exp\,(x_i'\beta)}{1+\exp\,(x_i'\beta)} = \frac{1}{1+\exp\,(-x_i'\beta)}$$

The empirical design includes defining an equation for estimating $PROB_{it}$ for each observation i that involves the following categories of explanatory variables:

$$PROB_{it} = x_{it}'\beta = \beta_0 + \beta_1 AQCA_{it} + \beta_2 MR_{it} + \beta_3 PL_{it} + \beta_4 LPC_{it} + \beta_5 LPR_{it} + \beta_6 FA_{it} + \beta_7 Size_{it} + \beta_8 STECON_{it} + u_i$$

where : $PROB_{it}$ is the binary dependent variable that takes a value of 1 for banks classified by the FDIC as failed banks and zero for surviving or successful (non-failed) banks; $AQCA_{it}$ are variables representing capital adequacy and asset quality; MR_{it} is a set of management risk variables; PL_{it} are variables that capture liquidity risk and bank earnings (profitability) potential; LPC_{it} are variables that represent loan portfolio composition measures; LPR_{it} capture loan portfolio risk measures; FA_{it} are variables that represent funding arrangements; $Size_{it}$ is a structural factor variable, specifically representing bank size; $STECON_{it}$ are economic variables that capture macroeconomic conditions at the state level; t = t denotes the period of time prior to bank failure. These variable categories and their specific factors are discussed in greater detail in Chapter 4.

The estimating model has six time period model versions. Each time period model utilizes a cross-sectional dataset compiled at specific points in time away from the actual occurrence of bank failure. The time period models considered in this study are:

1) 6-month model (two quarters before bank failure)

2) 12-month model (four quarters before bank failure)

3) 18-month model (6 quarters before bank failure)

4) 24-month model (8 quarters before bank failure)

5) 36-month model (12 quarters before bank failure)

6) 48-month model (16 quarters before bank failure).

In the different time period models, PROB is the identifier for banks that eventually failed during the entire sample period. For example, if Bank A is a bank that was declared bankrupt or insolvent in the 3rd quarter of 2009 while Bank B went into bankruptcy in the 1st quarter of 2009, and Bank C is a bank that successfully survived, the following delineation rules (table 3.1) are used in defining the observations for Banks A, B and C in the different cross-sectional time period models:

Table 3.1. Delineation of Bank Time Period Observations

Model	Bank A (Bankrupt in 3rd Qtr 2009)	Bank B (Bankrupt in 1st Qtr 2009)	Bank C (Surviving Bank)
6-month model	1st Qtr 2009	3rd Qtr 2008	2nd Qtr 2009[2]
12-month model	3rd Qtr 2008	1st Qtr 2007	4th Qtr 2008
18-month model	1st Qtr 2008	3rd Qtr 2007	2nd Qtr 2008
24-month model	3rd Qtr 2007	1st Qtr 2007	4th Qtr 2007
36-month model	3rd Qtr 2006	1st Qtr 2006	4th Qtr 2006
48 month model	3rd Qtr 2005	1st Qtr 2005	4th Qtr 2005

[2] Data for surviving banks are determined using the entire coverage of the dataset. The banking dataset used in this research extends to the last quarter of 2009. Hence, a surviving bank's data for the 6-month model, for instance, will be its 2nd quarter of 2009 financial conditions.

Pseudo-R^2 and In-sample classification accuracy are two ways to evaluate the fitness of the prediction model. R^2 is used to measure the goodness of fit in linear model, but its properties do not carry over to nonlinear regression. Thus, we use Pseudo-R^2, which is a measure of fit for nonlinear regression (binary regression model in this case) that attempt to mimic the normal R^2 measurement. The Pseudo-R^2 is also bounded between zero and one, with one representing a perfect fit and zero indicating that there is no relationship between the dependent variable and the regressors.

3.2.2 Prediction Methods

The method of in-sample classification accuracy predicts the outcomes ($PROB_{it}$) using the estimated coefficients and the existing datasets. It compares the predicted outcomes with actual outcomes through calculating the percentage of correctly classified observations. A higher percentage indicates a higher prediction efficiency of the model.

One important reason to study bank failures is to construct a bank failure prediction model that can be used to identify failure in the future. Out-of-sample forecasting is a method to test the predictive ability and explanatory power of the model. Similar to the in-sample classification, the out-of-sample forecasting also uses the estimated coefficients from cross-sectional logistic regressions, but applies them to an expanded dataset. The failed sample consists of all banks that failed in 2010, which is a year after the reckoning year for the failed bank observations in the bank prediction or early warning signals models. Then, out-of-sample forecasting uses the estimated coefficients from prediction model to predict the outcomes in 2010, and compare them with the actual outcomes in 2010. Similar to in-sample accuracy, higher percentage of correct classification implies higher prediction efficiency.

3.3 Technical Efficiency Analysis

A secondary analytical tool used in this study is the calculation and evaluation of technical efficiency as an indicator of the banks' financial health. The general approach for this type of analysis is the derivation of the levels of the banks' technical efficiency under a stochastic cost frontier framework. The technical efficiency scores are then used in an econometric regression that relates them, along with macroeconomic factors, to the probability of bank failure.

3.3.1 The Stochastic Frontier Model

Stochastic production frontier models were introduced by Aigner, Lovell, and Schmidt and Meeusen and Van den Broeck(Aigner, et al., 1976, Meeusen and van Den Broeck, 1977). Since then, these models become a popular subfield in econometrics and widely used in the efficiency measurement.

The nature of stochastic frontier problem can be described as follows: suppose a producer has a production function(x_{it}, β), where x_{it} is a vector of n inputs used by producer, and β is a vector of technology parameters to be estimated. In a world without error or inefficiency, in time t, the ith producer would produce

$$y_{it} = f(x_{it}, \beta)$$

where y_{it} is the observed scalar output of the producer.

A fundamental element of stochastic frontier analysis is that the firm produces less than it potentially might because of a degree of inefficiency, so the production frontier model can be written as

$$y_{it} = f(x_{it}, \beta)\xi_{it}$$

where ξ_{it} is the level of efficiency defined as the ratio of observed output to maximum feasible output for firm i at time t. ξ_{it} must lie in the interval (0,1]. ξ_{it} =1 shows that the ith firm achieves the optimal output with the technology embodied in the production function (x_{it}, β) , while $\xi_{it} < \mathbf{1}$ provides a measure of the shortfall of the observed output from the technology embodied in the production function(Kumbhakar and Lovell, 2003).

A stochastic component that represents the random shocks was added in the model so the frontier model can be rewritten as

$$y_{it} = f(x_{it}, \beta)\xi_{it}\exp(v_{it})$$

here $\exp(v_{it})$ denotes the random shocks. Although each producer faces different types of shock, we assume the shocks are random and described by a common distribution.

Taking the natural log of both sides, we write the model as

$$\ln(y_{it}) = \ln\{f(x_{it}, \beta)\} + \ln(\xi_{it}) + v_{it}$$

This study assumes that there are k inputs and the production function is linear in logs, and u_{it}=$\ln(\xi_{it})$ yields

$$\ln(y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{jit}) + v_{it} - u_{it}$$

This is also known as single-output Cobb-Douglas stochastic frontier function from, widely used by several studies (Battese and Coelli, 1993. Kumbhakar and Lovell, 2003. Coelli, et al., 2005). In the log-linear model, y_{it} is a scalar output, x_{jit} is a vector of kth inputs. β_j is the vector of the unknown technology parameters. v_{it} is a two-sided random-noise component, and u_{it} is a nonnegative cost inefficiency component, of the composed error term $\varepsilon_{it} = v_{it} - u_{it}$ (Kumbhakar and Lovell , 2003).

In this study, we apply the Stochastic Frontier Analysis (SFA) to measure both the failed banks and solvent banks' technical efficiency. Technical efficiency measures the ability of a firm to obtain optimal outputs from a given set of inputs (Drake and Hall, 2003). The efficiency score is in ratio form with observed output divided by potential maximum output. Thus, given the Cobb-Douglas stochastic frontier function, as introduced by Battese and Coelli(1993), the technical efficiency of the i_{th} bank in the t_{th} quarter is defined by:

$$TE_{it} = \frac{Observed\ output}{potential\ maximum\ output} = \frac{Y_{it}}{Y_{it}^{*}} = \frac{\exp\,(x_{it}\beta + v_{it} - u_{it})}{\exp\,(x_{it}\beta)} = \exp\,(-u_{it})$$

where Y_{it} is the frontier's output, and u_{it} denotes the specifications of the inefficiency component. The score of technical efficiency is between zero and one. The more efficiently a bank operates, the higher efficiency score is denoted. In this study, the post-estimation procedure of panel data stochastic frontier in STATA is applied to get the technical efficiency score.

3.3.2 Empirical Design

In the determining the role of technical efficiency in bank failure analysis, this study will employ an instrumental variable probit (IV Probit) approach. The IV Probit method used in this analysis uses maximum likelihood estimation technique that fits models with dichotomous dependent variables and endogenous explanatory variables. For a single endogenous regression, the model can be stated as:

$$z_{1i}^{*} = \alpha z_{2i}\alpha + \omega W_i + \mu_i$$
$$z_{2i} = \pi_1 W_i + \pi_2 V_i + v_i$$

where i=1, …, N, z_{1i}^{*} is a dichotomous dependent variable, z_{2i}^{*} a vector of endogenous variables, W_i is a vector of exogenous variables, V_i is a vector of instruments that satisfy conditions of instrumental exogeneity and relevance, α and ω are vectors of structural parameters and π_1 and π_2 are matrices of reduced form parameters. The z_{2i} equation is written in reduced form and both equations are estimated simultaneously using maximum likelihood techniques. As a discrete choice model, z_{1i}^{*} is not observed as the model instead fits z_{1i} =1 for $z_{1i} \geq 0$ and z_{1i} =0 for $z_{1i} < 0$.

In this analysis, the IV Probit model is formulated using technical efficiency (TE) scores (as the instrumented variable) and relevant macroeconomic variables. The idea is to test whether the TE scores, which shall involve instrument variables among the various bank financial performance factors used previously in the bank prediction models, are significant determinants of the probability of bank failure. Specifically, the model is estimated as follows:

$$PROB_{it}^{*} = \gamma_0 + \alpha TE + \omega W(MACRO) + \mu_i$$
$$TE = \pi_1 W(FV, ST) + v_i \quad ,$$

where $PROB_{it}^{*}$ is the same binary dependent variable defined in the bank failure prediction models; TE, the instrumented variable (z_{2i}^{*}) in this model, is the bank's technical efficiency score; FV and ST are the same set of financial measures and structural/demographic variables relating to the banks' financial performance, respectively, included in the bank failure prediction model; and MACRO, consisting of state-level unemployment growth rates (UNEMPL) and bankruptcy rates (BF) that capture the state level macroeconomic conditions. Separate regressions are made for 2009 and 2010 datasets. These years were chosen for this analysis as these were the years that recorded high numbers of bank failures.

CHAPTER IV

DATA AND VARIABLE DESCRIPTION

This section describes the data sources and the considerations for formulating the empirical model and developing the datasets. In the construction of bank failure prediction models, two types of data are used: CAMEL-type bank variables that are widely used in the previous studies (Arena, 2008, Cole and Gunther, 1998, Cole and Gunther, 1995, Thomson, 1991), and state specific variables to capture local economic conditions. For the stochastic cost frontier model we used in the efficiency measurement, input and output variables were defined from the bank call report data. The following sections describe these models and their data sources in greater detail.

4.1 Bank Call Report and State-Level Economic Data Sources

In order to determine early warning signals of bank failures among bank performance variables, several cross-sectional datasets are compiled in this study. The data for both failed banks and surviving banks are collected from the Call Reports Database published on the website of Federal Reserve Board of Chicago (FRB). The banking data are available through the banks' quarterly financial statements made publicly available by the FRB. This study's banking data are collected on a quarterly basis from January 2005 to September 2010, a time period that captures the favorable economic times prior to the onset of the current recession and the aggravation of the bank bankruptcy filings in 2009 and 2010.

For the non-failed sample, only banks that continuously reported their financial conditions in the dataset during the time period were included. Banks with unidentified state locations are also excluded in the sample to avoid complications when bank variables with state specific variables. Surviving or successful banks with missing values for any financial data being collected were discarded. Given these data restrictions, a total of 1109 banks were identified each year and included in the non-failed or successful bank sample.

In compiling the dataset, special attention was given to those banks that failed in 2009 and 2010 because these two years have the largest number of failure since 1992. FDIC records a total of 255 out of 297 failed banks to have been identified just in the two year period (2009-2010) – with 117 in 2009 and 138 in 2010 (Refer to table 4.1).

In addition to bank performance variables, this study also collected data from other sources that would reflect certain aspects of the local economic conditions during the recessionary period. These variables include state-level monthly unemployment rate data that were obtained from the Bureau of Labor Statistics and were converted to quarterly data. State-level numbers of bankruptcy were collected from Bankruptcy filing statistics, published online by American Bankruptcy Institute (ABI). These bankruptcy figures were available for business, non-business and even sectoral (including agriculture-related filings under Chapter 12 bankruptcy) filings. The Bureau of Economic Analysis (BEA) provided data on the state-level aggregation of personal incomes.

4.2 Categories of Variables for Bank Failure Prediction Models

In order to construct a model that can predict bank failure of all sizes, this study includes

Table 4.1. Number of failed banks in each year and in the sample		
	Number of banks	Number of banks in sample
2005	0	0
2006	0	0
2007	3	0
2008	25	0
2009	140	117
2010	157	138

proxy variables based on balance-sheet and income data from Call Reports. Some of the explanatory variables are selected to be proxies for the components of the CAMEL rating system, which is used by regulators during on-site examinations to determine a bank's financial conditions. These variables are summarized and defined in table 4.2.

4.2.1 The Dependent Variable and Definitions of Time Periods

The different cross-sectional models for different time period bank failure prediction models all have the same version of the dependent variable. PROB is a binary variable for bank failure that takes on a value of 1 for failed banks and 0 for surviving (non-failed) or successful banks.

4.2.2 Asset Quality and Capital Adequacy (AQCA)

These measures include RWCAPRATIO, the risk-weighted capital ratio, which is defined as the ratio of tier 1 capital to risk-weighted assets, where tier 1 capital include common stock, common stock surplus, retained earnings, and some perpetual preferred stock(Estrella, et al., 2000). This variable has been used as proxy for capital adequacy in CAMEL rating system.

Another variable considered in this category is LOANHER, measured as the loan portfolio diversification index. This index captures the extent of diversification of the bank's risky asset (loans) among various loan types and, thus, is considered another for asset quality and portfolio risk in CAMEL. The index was developed using the Herfindahl measurement method where the index was constructed from taking the sum of squares of various components of the loan portfolio:

Table 4.2. Definitions of Variables for the bank failure prediction model

Variables	Descriptions
Dependent variable	
PROB	Dummy variables, equals to one for failed banks and zero for non-failed banks.
Explanatory variables	
RWCAPRATIO	Risk-weighted capital ratio
AGNR	Aggregate past due/non-accrual agricultural non-real estate loans/total loans
AGR	Aggregate past due/non-accrual agricultural real estate loans/total loans
INDUS	Aggregate past due/non-accrual Commercial & Industrial loans /total loans
CONSUM	Aggregate past due/non-accrual Consumer loans /total loans
LOANHER	Loan portfolio Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial & industrial loans, and agricultural loans.
AGTOTAL	Agricultural loans / total loans
CONSTOTAL	Consumer loans/total loans
INDUSTOTAL	Commercial & Industrial loans / total loans
RETOTAL	Real Estate loans/total loans
LIQM1	Non-deposit liabilities /cash and investment securities
LIQM2	Total loans/ total deposits
OVERHEAD	Overhead costs/total assets
INSIDELN	Loans to insiders/total assets
PROFIT	Return on assets
SIZE	Natural logarithm of total assets
PURCHASEDTL	Purchased funds to total liabilities
DEPLIAB	Total deposits/ total liabilities
GAP	Duration GAP measure
UNEMRATE	Percentage change of unemployment rate
BF	Business failure ratio

$$\boldsymbol{LOANCHER} = \sum \left(\frac{Real\ Estate\ Loans}{Total\ Loans}\right)^2 + \left(\frac{Loans\ to\ depository\ institutions}{Total\ Loans}\right)^2 + \left(\frac{Individual\ Loans}{Total\ Loans}\right)^2 + \left(\frac{Commercial\ and\ Industrial\ Loans}{Total\ Loans}\right)^2 + \left(\frac{Agricultural\ Loans}{Total\ Loans}\right)^2$$

This ratio will take a value closer to one if the bank's loan portfolio is heavily specialized in one or two of the loan components. In other words, a higher index value indicates greater product or loan specialization. A smaller ratio indicates a more diversified loan portfolio.

In the above equation, the following ratios representing the various types of loan products were used: real estate loans to total loans, loans to depository institutions to total loans, loans to individuals to total loans, commercial and industrial loans to total loans, and agricultural loans to total loans.

4.2.3 Management Risk (MR)

OVERHEAD and INSIDELN are proxies for management risk in the CAMEL rating systems. OVERHEAD is a measure of operating efficiency that was introduced in the model in a ratio form (dividing overhead costs by total assets). Using "Aggregate amount of all extensions of credit to executive officers, directors, and principal shareholders" as a proxy for the insider loan, we use the ratio of insider loan to total assets (INSIDELN) to capture another form of management risk: fraud or insider abuse.

4.2.4 Profitability and Liquidity (PL)

PROFIT, or return on assets, is the proxy for the banks' earnings capability in the CAMEL rating system. To calculate return on assets, we need to construct the net income after taxes to total assets ratio. However, the item net income after taxes are no longer available in Call Report, and so item "Undivided profits and capital reserves" was used instead.

Two types of liquidity measures were added to the model as proxies for liquidity risk. LIQM1 was calculated by dividing non-deposit liabilities with cash and investment securities. LIQM2 was calculated by dividing total loans with total deposits.

4.2.5 Loan Portfolio Composition Measures (LPC)

Measures that capture the banks' loan exposure to different industry sectors are also included in the analyses. AGTOTAL, CONSTOTAL, INDUSTOTAL and RETOTAL are ratios of loans extended to the agricultural, consumer, industrial and real estate industries, respectively. The ratios were calculated by dividing the total loan portfolio for each client sector or group to the total loan portfolio of the bank.

AGTOTAL is an intentional variable included in the analyses in order to determine the influence of credit exposure to the seemingly riskier clients in the farm sector experiencing relatively greater uncertainties in their business operations. CONSTOTAL is an interesting variable to monitor as the latest trends in financing indicate the surge of consumer credit as finance companies recklessly flood the markets with credit card financing offers. INDUSTOTAL is another variable to watch as this would provide insights on the banking industry's exposure to the sector of the economy that could help stimulate growth. RETOTAL is the most interesting variable to track in these analyses as the real estate industry has been identified as one of the significant precursor and instigator of the economic downswing.

4.2.6 Loan Portfolio Risk Measures (LPR)

Beyond the previous category of loan portfolio-based variables, this study also considers loan portfolio risk measures that are expected to even shed more light into the causes of bank failures. This study differentiates itself from the previous bank failure models that only considered one single measure of loan portfolio risk – usually the overall loan delinquency rate. In this study, the loan delinquency rates that capture loan portfolio risk are measured for certain categories of loan exposures: agricultural non-real estate loans (AGNR), agricultural real estate loans (AGR), commercial & industrial loans (INDUS), and consumer loans (CONSUM). These portfolio risk ratios are calculated by aggregating such loan delinquency figures as "Past due up to 89 days", "Past due 90 plus days", and "Nonaccrual or charge offs" together for each loan category (as enumerated above) and dividing the total delinquencies by the aggregate value of the loan portfolio. The delinquency rates for the agricultural loan portfolio were separated for real estate and non-real estate loans in order to isolate the effects of real estate loan exposures to this industry and determine whether the agricultural sector contributed to the popular claim that real estate delinquencies, in general, are being suspected as the significant precursors of recession.

4.2.7 Funding Arrangements (FA)

The next three early warning system variables represent the funding arrangements or strategies employed by banks. PURCHASEDTL, purchased liabilities as a percentage of total liabilities, is used to reflect the share of liabilities purchased from national market, as suggested by Belongia and Gilbert(Belongia and Gilbert, 1990). Core deposits were used as proxy for purchased liabilities, which consist of deposits collected at domestic offices. These deposits include transaction accounts, non-transaction savings deposits, and total time deposits less than

$100,000(Black, et al., 2007). DEPLIAB, was calculated by taking the ratio of total deposits to total liabilities.

This study also considers duration gap, GAP, which is a commonly used tool to measure interest-rate risk. Previous studies of bank failure prediction usually ignore this variable. Belongia and Gilbert tried to introduce the concept in their study by specifying a measure calculated by taking assets with maturities under one year minus liabilities with maturities under one year, and dividing the difference by total assets(Belongia and Gilbert, 1990). However, this variable did not figure as a significant factor in the model. In this study, instead of using the definition from Belongia and Gilbert, the definition given by Blasko and Sinkey[3] is instead used. Just as in their study, in this study, GAP is defined as the difference between rate-sensitive assets and rate-sensitive liabilities(Blasko and Sinkey, 2006). This approach is more appropriate to calculate GAP when using the Call Reports dataset since all the variables they used can be directly found from the dataset.

4.2.8 Structural Factor (SIZE)

SIZE variable was included in the model by taking the natural logarithm of total assets. This variable was added to the failure prediction model to account for the "too big to fail" doctrine. The expectation in this doctrine is that banks that have grown tremendously have managed to

[3] In their study, Blasko and Sinkey (2006) define rate sensitive assets = (Federal funds sold) + (Securities purchased under agreements to resell) + (Customer's liability) + (Trading assets) + (Fixed and floating debt securities maturing or repricing within 12 months) + (Fixed and floating loans maturing or repricing within 12 months); rate sensitive liabilities = (Federal funds purchased) + (Securities sold under agreements to repurchase) + (Bank's liability on acceptances executed and outstanding) + (Trading liabilities) + (Other borrowed money) + (Demand notes issued to the U.S. Treasury) + (Time and saving deposits) – (Large long-term time deposits).
And GAP = rate sensitive assets – rate sensitive liabilities + (Small longer-term deposits).

install coping mechanisms or accumulated enough financial agility and endurance that can weather any threats to their survival and business success.

4.2.9 State Economic Variables (STECON)

Again, as mentioned earlier, this study further extends the previous bank failure prediction (early warning) models by considering variables that capture the macroeconomic conditions at the state level. UNEMRATE, is the quarterly percentage change of state-level unemployment rate. The data of U.S. bankruptcy filings was also used as a proxy for general business conditions of each state. BF, was calculated by aggregating each state's business filings and non-business filings together, and dividing the total by the number of total filings of all states. This variable is also on quarterly basis. CH12 is a more specific measure of business failures as it accounts only for the farm business bankruptcies filed under the Chapter 12 provision of the American Bankruptcy Law. CH12 was calculated by dividing the total number of Chapter 12 filings and the total number of bankruptcies in each state in each quarter. PI is the quarterly percentage change in the state's average personal income. This variable is intended to further capture general economic conditions at the local level.

The summary statistics for the selected variables are listed in table 4.3.

4.3 Technical Efficiency Analysis Data

In contrast to the cross-sectional analysis in the bank failure prediction models, this study's technical efficiency analysis utilizes a panel data collected from the Call Report Database during the two years when majority of the bank failures were experienced (2009 and 2010). The same data filtering criterion used in the bank prediction analysis was applied to the non-failed banks.

Table 4.3. Data Summary for Bank Failure Prediction Model

Variable	Mean	Std Dev	Minimum	Maximum
RWCAPRATIO	0.1530940	0.1249180	-0.1151116	4.2487322
AGNR	0.0019650	0.0067908	0	0.3761140
AGR	0.0028566	0.0060035	0	0.0973604
INDUS	0.0049533	0.0074063	0	0.1516214
CONSUM	0.0030429	0.0045456	0	0.1206132
LOANHER	0.5518798	0.1626507	0.0027596	1.0000000
AGTOTAL	0.0913351	0.1332089	0	0.8123182
CONSTOTAL	0.0825909	0.0718453	0	0.8916693
INDUSTOTAL	0.1344470	0.0805220	0	1.0000000
RETOTAL	0.6771947	0.1735415	0	1.0000000
LIQM1	0.2644837	0.8537944	0.000641425	87.3231707
LIQM2	0.8180226	0.2270182	0.0349895	18.5314417
OVERHEAD	0.0122925	0.0070465	-0.0015692	0.1866298
INSIDELN	0.0128210	0.0147672	0	0.1838665
PROFIT	0.0581081	0.0476434	-1.1943348	0.2913457
SIZE	12.0436089	1.1306911	8.3884503	16.7374802
PURCHASEDTL	1.0880538	0.1431893	0.0317430	1.7592494
DEPLIAB	0.9243575	0.0741731	0.0317430	0.9996039
GAP	-0.0773074	0.1927683	-0.7182902	0.9225336
UNEMRATE	0.0226906	0.0737394	-0.5392857	0.3790850
BF	0.0262317	0.0207329	0	0.1688684

In this analysis, a smaller sample of non-failed banks from Call Reports was randomly selected in a manner that ensures the panel data stochastic frontier approach can successfully converge to the log-likelihood value. In this case, 800 non-failed banks and 258 failed banks were selected, with 23227 observations in total across 6 years.

The stochastic cost frontier framework usually requires two general data categories: bank outputs, and bank inputs. Bank output data used in this study include Agricultural loans (y_1), Non-agricultural loans (y_2), Consumer loans (y_3), Fee-based financial services (y_4), and Other assets in the banks' balance sheets that could not be categorized under the previous output categories (y_5). The single output in the Cobb-Douglas frontier functional form is calculated from the aggregation of the above outputs. The input data categories considered are Number of full time employees(x_1), Premises and fixed assets(including capitalized leases) (x_2), Federal funds purchased and securities sold under agreements to repurchase plus Total time deposits of $100,000 or more($x_3$), and Total deposits($x_4$). These were collected from the Call Report dataset.

Most bank efficiency studies in corporate finance literature consider only the above three data categories. In this study, the stochastic cost function model is extended to include two important variables: loan quality index (z_1) and financial risk index (z_2). These additional variables are intended to introduce a risk dimension to the efficiency model. The index z_1 is calculated from the ratio of non-performing loans to total loans to capture the quality of bank's loan portfolios. The index z_2 is based on banks' capital to asset ratio, which is used by many studies as a proxy for financial risk. The detailed variable definitions are presented in table 4.4.

Table 4.4. Definitions of Variables for the stochastic cost frontier

Variable	Description
Output	
y_1	Agricultural loans
y_2	Non-agricultural loans, composed from real estate loans, commercial and industrial loans, and lease financing receivables
y_3	Consumer loans
y_4	Fee-based financial services
y_5	Other assets
Input	
x_1	Number of full-time equivalent employees on payroll at end of current period
x_2	Premises and fixed Assets(Including capitalized leases)
x_3	Quarterly average of federal funds purchased and securities sold under agreements to repurchase
	Total time deposits of $100,000 or more
x_4	Total deposits
Exogenous	
z_1	Ratio of non-performing loans to total loans (NPL)
z_2	Ratio of banks' capital to assets.

CHAPTER V

RESULTS AND IMPLICATIONS

5.1 Bank Failure Prediction Model

In determining early warning signals for predicting bank failures, logistic regression techniques were applied to several time period models dating back from 6 months to 48 months before a bank is declared insolvent by the FDIC, which is otherwise known in this study as bank failure. This portion of the analysis considers 6 time period models: 6months, 12 months, 18months, 24 months, 36 months, and 48 months prior to failure. The in-sample prediction for these 6 model versions is undertaken using a database of 95 banks that failed in 2009 and 1,180 banks that have survived and continued operations through that year.

Table 5.1 summarizes the logistic regression results for all time period model versions, which are useful for determining the relative significance of variables and their directional (positive or negative) relationship with the dependent variable. Table 5.2 provides the results for marginal effects that show the magnitude of influence the explanatory variables have on the dependent variable. The following subsections discuss specific results pertaining to the categories of explanatory variables with significant results and implications in the bank failure prediction models:

Table 5.1. Cross-sectional logit regression results for bank failure prediction model

	Months to failure after Call Report issued					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
RWCAPRATIO	-79.49***	-58.35***	-24.05**	-2.69	1.04	0.23
	(19.62)	(15.07)	(11.49)	(2.84)	(4.38)	(1.61)
AGNR	43.56	-50.04	-661.713	-477.03	-1317.93	-122.40
	(27.85)	(84.37)	(685.18)	(474.77)	(1088.49)	(287.33)
AGR	-14.43	13.91	7.80	-124.45	-328.72	-196.33
	(24.34)	(50.27)	(58.16)	(139.04)	(235.37)	(213.78)
INDUS	24.08	91.77**	29.15	72.69**	18.98	34.35
	(19.89)	(43.30)	(18.45)	(32.85)	(33.67)	(31.04)
CONSUM	247.84***	201.24*	122.96**	-34.29	18.98	34.35
	(69.65)	(106.13)	(52.89)	(137.76)	(33.67)	(31.04)
LOANHER	9.92*	1.89	2.98	2.32	-4.43	1.38
	(5.44)	(6.53)	(3.63)	(3.07)	(4.60)	(3.52)
AGTOTAL	-9.07	-21.85	-11.05	-3.12	7.96	0.18
	(12.25)	(10.67)	(9.04)	(8.55)	(10.84)	(8.03)
CONSTOTAL	-17.76	-41.34**	-41.02**	-26.37**	-19.31	-14.28
	(11.68)	(15.34)	(12.78)	(13.20)	(13.46)	(10.19)
INDUSTOTAL	-13.97	-24.85**	-7.47	-4.89	6.64	3.24
	(10.69)	(11.22)	(7.85)	(8.51)	(10.07)	(8.21)
RETOTAL	-10.21	-14.51	-5.97	-2.43	16.02	5.62
	(13.22)	(13.27)	(8.72)	(9.14)	(13.00)	(9.39)
LIQM1	0.38	0.63	0.25	0.28	-0.72	-0.82
	(0.59)	(0.48)	(0.24)	(0.31)	(1.12)	(0.51)
LIQM2	-7.79**	-4.70**	-0.95	-1.15	1.23	-0.32
	(2.49)	(1.54)	(1.83)	(1.67)	(1.32)	(0.61)
OVERHEAD	66.130	-115.50**	23.10	-98.63**	-113.36**	-132.03***
	(78.89)	(33.24)	(65.56)	(31.55)	(46.51)	(28.14)
INSIDELN	-1.67	-1.15	12.84	-1.69	5.89	0.51
	(26.45)	(12.20)	(10.34)	(10.32)	(10.13)	(9.67)
PROFIT	-10.67	-32.88**	-4.08	-22.42***	-23.38***	-21.80***
	(10.22)	(5.99)	(3.15)	(6.18)	(5.14)	(4.01)
SIZE	0.33	-0.33	-0.04	0.03	0.05	-0.14
	(0.26)	(0.21)	(0.18)	(0.18)	(0.20)	(0.15)
PURCHASEDTL	5.57*	6.92***	1.49	3.07**	2.47*	4.20**
	(3.24)	(2.00)	(1.61)	(1.52)	(1.42)	(1.60)
DEPLIAB	-20.09**	-16.47***	-8.77*	-7.09*	-9.32**	-12.48**
	(9.57)	(4.47)	(4.62)	(3.87)	(3.94)	(3.94)
GAP	9.24***	6.81***	4.89***	4.35***	4.14***	4.74***
	(2.18)	(1.35)	(1.11)	(1.02)	(0.96)	(0.99)
UNEMRATE	30.62**	-13.62**	-31.09**	17.10***	16.99**	4.23*
	(9.10)	(5.12)	(5.86)	(4.75)	(5.53)	(2.31)
BF	30.32**	32.18***	42.84***	13.36**	32.64***	25.98***
	(14.68)	(8.39)	(8.93)	(6.73)	(7.86)	(7.37)
Constant	17.93	37.96**	14.00	5.80	-5.68	4.49
	(12.32)	(12.25)	(8.90)	(8.50)	(11.50)	(9.06)

Note

*** Significantly different from zero at the 1% level. ** Significantly different from zero at the 5% level.

* Significantly different from zero at the 10% level. Standard errors are reported in the parentheses.

Table 5.2. Marginal Effects of the Logit Results

	Months to failure after Call Report issued					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
RWCAPRATIO	-0.73***	-1.15***	-0.76**	-0.09	0.04	0.01
	(0.16)	(0.23)	(0.34)	(0.10)	(0.15)	(0.06)
AGNR	0.40	-0.99	-20.90	-16.63	-44.15	-4.61
	(0.25)	(1.67)	(21.64)	(16.54)	(36.46)	(10.81)
AGR	-0.13	0.27	0.25	-4.34	-11.01	-7.39
	(0.22)	(0.99)	(1.84)	(4.85)	(7.89)	(8.04)
INDUS	0.22	1.81**	0.92	2.53**	0.64	1.29
	(0.18)	(0.85)	(0.58)	(1.14)	(1.13)	(1.17)
CONSUM	2.27***	3.97*	3.88**	-1.20	4.30	0.32
	(0.64)	(2.10)	(1.67)	(4.80)	(4.24)	(5.13)
LOANHER	0.09*	0.04	0.09	0.08	-0.15	0.05
	(0.05)	(0.13)	(0.11)	(0.11)	(0.16)	(0.13)
AGTOTAL	-0.08	-0.43**	-0.35	-0.11	0.27	0.001
	(0.11)	(0.20)	(0.29)	(0.30)	(0.37)	(0.30)
CONSTOTAL	-0.16	-0.82**	-1.30**	-0.92**	-0.65	-0.54
	(0.10)	(0.29)	(0.41)	(0.45)	(0.45)	(0.38)
INDUSTOTAL	-0.13	-0.49**	-0.24	-0.17	0.22	0.12
	(0.09)	(0.21)	(0.25)	(0.39)	(0.34)	(0.31)
RETOTAL	-0.09	-0.29	-0.19	-0.08	0.54	0.21
	(0.12)	(0.25)	(0.28)	(0.32)	(0.44)	(0.35)
LIQM1	0.003	0.01	0.01	0.01	-0.02	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
LIQM2	-0.07***	-0.09**	-0.03	-0.04	0.04	-0.01
	(0.02)	(0.03)	(0.06)	(0.06)	(0.04)	(0.02)
OVERHEAD	0.61	-2.28***	0.73	-3.44**	-3.80**	-4.97***
	(0.72)	(0.65)	(2.07)	(1.10)	(1.57)	(1.05)
INSIDELN	-0.02	-0.02	0.41	-0.06	0.20	0.02
	(0.24)	(0.24)	(0.33)	(0.36)	(0.34)	(0.36)
PROFIT	-0.10	-0.65***	-0.13	-0.78***	-0.78***	-0.82***
	(0.09)	(0.09)	(0.10)	(0.22)	(0.19)	(0.16)
SIZE	0.003	-0.01*	-0.001	0.001	0.002	-0.01
	(0.002)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
PURCHASEDTL	0.05*	0.14***	0.05	0.11**	0.08*	0.16**
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
DEPLIAB	-0.18**	-0.033***	-0.28*	-0.25*	-0.31**	-0.47***
	(0.09)	(0.09)	(0.14)	(0.14)	(0.13)	(0.15)
GAP	0.08***	0.13***	0.15***	0.15***	0.14***	0.18***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
UNEMRATE	0.28**	-0.27**	-0.98***	0.60***	0.57***	0.16*
	(0.10)	(0.09)	(0.17)	(0.16)	(0.18)	(0.09)
BF	0.28**	0.64***	1.35***	0.47**	1.09***	0.98***
	(0.14)	(0.16)	(0.28)	(0.23)	(0.27)	(0.28)

Note:

*** Significantly different from zero at the 1% level.

** Significantly different from zero at the 5% level.

* Significantly different from zero at the 10% level.

Standard errors are reported in the parentheses.

5.1.1 Asset Quality and Capital Adequacy

Based on the result summaries, one of the notable results was the significance of RWCAPRATIO, the risk-weighted capital ratio is a measure of bank's tier 1 core capital expressed as a percentage of risk weighted assets, which is being used by the FDIC to identify banks that are still solvent, those that need to be warned about possible insolvency, and those that are eventually closed down because of critically insolvent conditions. This ratio determines the capacity of the bank in terms of facing certain risks such as credit risk, and operational risk. This study's results indicate that RWCAPRATIO is a significant negative determinant (and predictor) of bank failure from 6 months until as long as 18 months prior to failure. The coefficients of this variable tend to become insignificant at longer time lags, which may suggest of its reliability as a predictor of financial stress over the short-run, but not over longer time horizons.

The loan diversification variable measured using the Herfindahl index approach was also included in Thomson's study and did not fare well as in his regression models. In this study, this variable is also barely significant in the 6-month model as its p-value shows significance under the 10 percent confidence level. The positive sign of the index in that model is intuitively reasonable as loan portfolio diversification is normally regarded as a risk-reducing strategy and, thus, could provide a bank with opportunities to enhance revenue-earning potentials with risks spread out across industries with offsetting risk profiles. As larger values of the index are indicative of greater product specialization tendencies, then the significant positive coefficient result in the 6-month model suggests that diversification indeed helps minimize the probability of bank failure.

5.1.2 Loan Portfolio Composition

Pursuant to the verified effectiveness of the loan portfolio diversification strategy, the loan portfolio composition variables identify the sectors that banks should consider in their loan servicing operations. The regression results indicate that banks may consider loan exposures to their consumer credit clientele (CONSTOTAL) from 1 to 2 years prior to bank failures. Loan exposures to agricultural (AGTOTAL) and industrial (INDUSTOTAL) may be considered around 1 year before the onset of bank failures. These variables are negatively signed, which suggests that an increase in the portfolio of these loans will decrease the probability of failure.

5.1.3 Loan Portfolio Risk

Among the portfolio risk variables (AGNR, AGR, CONSUM and INDUS, which are loan ratios of past due/ nonaccrual loans), the most notable result that applies to this study's special focus is the insignificance of both the non-real estate and real estate delinquency ratios for agricultural loans (AGNR and AGR) across all time period models. This suggests that agricultural loan ratios cannot be used as indicators for predicting bank failure. This finding is important because it confirms our contention that exposure to clients engaged in seemingly riskier and more uncertain agribusiness operations does not really pose as a risk or enhances a bank's tendency to fail.

On the contrary, the delinquency loan ratios for consumer loans (CONSUM) and commercial/industrial loans (INDUS) are significant positive regressors in some time period models. CONSUM is a significant determinant or predictor of bank failure from 6 months up to

18 months prior to bank failure, while INDUS is a significant bank failure predictor around 12 and 24 months before bank insolvency.

The marginal effects results for these variables provide interesting insights and implications. As shown in table 5.2, a 1 percent increase in the industrial loan delinquency ratio will increase the probability of bank failure by 253% around 24 months before bank failure. At about a year before bank failure, the marginal effect of INDUS is 1.81. The magnitude of the marginal effects for CONSUM is even larger. In fact, the CONSUM marginal effects are one of the largest among those calculated for the significant predictors of bank failure. Based on the results (table 5.2), a 1% increase in the consumer loan delinquency ratio could increase the probability of bank failure by 227%, 397% and 388% around 6, 12, and 18 months, respectively, before the occurrence of bank failure. It is worth noting that most consumer loans extended by commercial banks are through credit cards and other revolving credit plans.

5.1.4 Management Risk

Variables that capture management risk and insider abuse are expected to be positively related to the probability of bank failure. The insider loan (INSIDELN) should be positively related to the failure because this measure can capture alleged bank decisions that are not usually governed by more rational, objective standards of business decision-making, such as the extension of credit. However, in contrast to the results obtained in previous studies, the coefficients for this variable have remained consistently insignificant across all the time period models.

On the other hand, the overhead cost ratio (OVERHEAD) variable has turned up negative and significant results in almost all time period models (except for the 6 month and 18 month models). These results indicate that higher overhead cost ratios actually decrease the probability of failure. While this result obviously defies the logical expectation of a significant positive coefficient, this contrasting result can be attributed to some plausible strategic moves of banks during the recessionary period. When faced with financial difficulty, especially illiquid conditions, banks may have the tendency to resolve the operating constraint by selling low-risk assets (like Treasury securities) that are relatively more easily marketable. As a result of such probable coping mechanism, the bank loses its asset base (denominator of the OVERHEAD ratio) while at the same time, overhead costs (ratio's numerator) could possibly be rising as a result of higher degrees of operating inefficiency produced by less prudent operating decisions. Thus, the net effect of these two trends would be the positive relationship between increasing OVERHEAD ratios and the probability of bank failure.

5.1.5 Profitability and Liquidity

Two measures of liquidity (LIQM1, LIQM2) are included as regressors in the models to capture different facets of bank liquidity. LIQM1 is measured in this study in the same fashion suggested by Thomson(Thomson, 1989) – i.e. the ratio of non-deposit liabilities to cash and investment securities. This variable captures liquidity that is attributed to more costly sources of funds (non-deposit liabilities) as opposed to the cheaper deposit sources. As such, this liquidity-enhancing option, while favorable to bank liquidity conditions, is actually unfavorable in terms of enhancing profit potentials and, hence, maximizing equity gains for the bank. Thus, this variable is expected to be positively related to the probability of bank failure. In this study, this variable's coefficients across all time period models have been insignificant.

The other liquidity measurement, LIQM2, calculated as the loan-to-deposit ratio, produced more significant results for the 6-month and 12-month models. The loan-to-deposit ratio captures the bank's financing strategy where bank loans are funded through deposits – which is an ideal, logical operating decision for banks. An upswing in this ratio may suggest that a bank has less of a cushion to fund its growth and to protect itself against a sudden recall of its funding (Feldman 1998). Thus, it should be positively related to the bank failure. The unexpected result for this variable (significantly negative) may indicate that this variable is a poor proxy of liquidity.

PROFIT is calculated as the return on assets and should be negatively related to the probability of bank failure. The significant negative coefficients of PROFIT in all time period models (except for the 6-month and 18-month models) indicate that the erosion of bank profits can be a strong determinant (and eventual predictor) of the probability of bank failure.

5.1.6 Funding Arrangements

The two funding arrangements variables capture two ways that bank may consider in procuring funds. On one hand, the bank can turn to the national markets for "purchased liabilities" where it is a mere price taker. On the other hand, it can rely on the local market through deposit generation where it has some influence on the pricing of such funds.

PURCHASEDTL, defined as the percentage of purchased liabilities among total liabilities, captures the national market option for sourcing funds. As described by Belongia and Gilbert(Belongia and Gilbert, 1990), the liabilities purchased from national market will have higher interest rate**.** So holding other factors constant, a bank with a higher average interest rate on its liabilities will face a higher probability of loss. The coefficient results are robust across all time period models (except for the18 month-model) with significant positive results, indicating that banks are more likely to fail when exposed to the higher interest rate risk.

On the other hand, the coefficient for DEPLIAB is negative and significant in all time period models. These results are consistent with the expectation that banks' tendency to thrive in their businesses are enhanced by their ability to maximize the generation of deposits to fund their business funding requirements.

A third measure, duration GAP measurement, is also included in the analysis to further investigate interest rate risk issues. The significant positive coefficient of GAP that all time period models produced is consistent with logical expectations as higher GAP values are associated with higher interest rate risk. These results therefore imply that the probability of bank failure is positively related to the likelihood or incidence of higher interest rate risk or the banks' greater sensitivity to interest rate change. When banks hold a greater proportion of more interest rate sensitive assets and liabilities, the bank is more likely to experience failure.

5.1.7 Structural Factor

SIZE is the natural logarithm of total assets hold by banks. The size factor has two contrasting arguments. On one hand, the "too big to fail" doctrine asserts that larger banks may have already solidified their hold on the markets and thus could easily expand operations and enhance revenue generation potentials. Larger banks could have already established more coping mechanisms that could be relied on in times of financial distress. However, as argued by

Thomson(1989), large banks have accumulated more complicated portfolio and transactions that may be difficult to manage and thus would possibly lead to a bank's tendency to incur operating losses. This viewpoint contends that the cost of failure could be much greater for larger banks than for smaller banks.

The results of this study coincide with the former line of thought. The SIZE variable was at least significantly negatively related to the probability of failure in the 12-month model, while remaining insignificant in the other time period models.

5.1.8 State Economic Variables

The original list of economic variables includes unemployment rate, bankruptcy rate, changes in personal incomes (PI), and farm-related bankruptcy (Chapter 12) rates. However, PI and Chapter 12 variables were dropped from the final version of the estimating equations due to collinearity problems.

The results for the state economic variables are somewhat mixed. The unemployment rate is expected to be positively related to the probability of bank failure for a healthy economic condition should have a positive effect on the banking industry. But in our analysis, percentage change of state-level unemployment rate (UNEMRATE) has mixed signs, which is not a new result. Thomson, in his study, also obtained the same result suggesting a negative relationship between bank failure and unemployment rate. He explained his results by citing the increased political constraints as explanation. Specifically, he contends that increased political constraints prevent insolvent banks from being closed in the depressed regions(Thomson, 1991).

On the other hand, the results for the state-level bankruptcy filing ratio (BF) variable are more logically acceptable. BF is a strong indicator or predictor of bank failure across all time period models, i.e. from the 6-month even up to 48 month-model. The negative and significant coefficients imply that a higher incidence of business or non-business failures or bankruptcies in each state would further depress the general economic conditions that would, in turn, influence the surge of bank failures.

5.1.9 Important Early Warning Signals

Based on the foregoing discussions, important early warning signals are then identified by period to stress the importance of paying attention to such factors long before they cause more serious operating problems for the banks. The following subsections categorize the early warning signals according to time periods, or the length of time before the actual occurrence of bank failures (as summarized in table 5.3).

5.1.9.1 Three to Four Years Prior to Bank Failure

The 36-month and 48-month time period models (tables 5.1 and 5.2) yielded results that suggest that around this period of time prior to bank failure, the early warning signals (i.e. factors that would increase the likelihood of bank failure) include a deterioration in bank profits (PROFIT), asset and liability portfolios with high interest rate risk (GAP), funding arrangement decisions that lead banks to rely more on the more costly fund sources in the national market rather than deposits (PURCHASEDTL and DEPLIAB), a tendency of banks to trim down assets through sale of low-risk assets for the sake of liquidity (OVERHEAD), and the deterioration of general macroeconomic conditions (BF and UNEMRATE). This set of factors came up as significant regressors in those two time period models.

5.1.9.2 Two Years Prior to Bank Failure

Around two years prior to bank failure, banks should be wary about almost the same set of factors identified in as early warning signals around 3 to 4 years prior to bank failure. However, there are new signals that banks should also pay attention to around 18 to 24 months before critical insolvency is experienced. The delinquency rates of large commercial, industrial loans (INDUS) and consumer loans (CONSUM) now become important predictors of bank failure. In the 18-month time period model, the risk-weighted capital ratio (RWCAPRATIO), which is used by FDIC for classifying solvent and insolvent banks, also becomes a significant determinant or predictor of bank failure.

5.1.9.3 One Year Prior to Bank Failure

As the time period draws closer to the incidence of bank failure, the early warning signals identified earlier (2 to 4 years) remain the same. Specifically, profit trends, interest rate risk issues, prevailing macroeconomic conditions, funding arrangement decisions, asset sale decisions, worsening delinquency records of industrial and consumer loans and deterioration in capital adequacy, especially risk-weight capital, are significant predictors of bank failures.

5.1.9.4 Six Months Prior to Bank Failure

In the time period model closest to the actual occurrence of bank failure, the early warning signals consist of most of those identified in the earlier time period models. As bank failures become more of a certainty about six months before they actually occur, the important signals of failure include funding arrangement decisions favoring the more costly funds from the national markets, increase in consumer loan delinquencies, deterioration of risk-weighted capital ratios, and the persistence of unfavorable macroeconomic conditions.

5.1.10 In-Sample Classification Accuracy

After each regression run, in-sample forecasting is also done to verify the model's reliability in classifying the bank observations among failed and non-failed categories given the previous estimation results. Table 5.3 reports the overall classification accuracy for all time period models, along with each model's type I and type II error, and Pseudo R^2. In this case, type I error occurs when a failed bank is misclassified as a non-failed banks. On the other hand, type II error occurs when a non-failed bank is incorrectly classified as failed banks. There is a trade-off between the probability of type I error and type II error, so it is impossible to reduce both simultaneously. The logit model classifies a bank as failed if the predicted value of the dependent variable exceeds a exogenously set probability cutoff point(Thomson, 1991). That is, the y can be segmented into populations $y \geq y_c$ and $y < y_c$, where y_c is an arbitrary value bounded between zero and one. So the predicted y is classified if $y \geq y_c \mid y = 1$ or $y < y_c \mid y=0$. In this study, we use 0.5 as cutoff point, which is typically used by many researchers.

As shown in table 5.4, the overall classification accuracy ranges from 95.11 to 98.59, where the accuracy level is highest for time period models are closer to the occurrence of bank failure. The overall accuracy level tends to diminish as the time period model moves farther away from the experience of bank failure. Specifically, the accuracy rate is 98.59% for the more current 6-month time period model and 95.11% for the 48-month period model.

Table 5.3. Important Early Warning Signals of Eventual Bank Failure		
3 to 4 Years Prior to Failure	**About 2 Years Prior to Failure**	**6 to 12 Months Prior to Failure**
Costly Funding Arrangements	Costly Funding Arrangements	Costly Funding Arrangements
Increasing Interest Rate Risk	Increasing Interest Rate Risk	Increasing Interest Rate Risk
Declining Profits	Declining Profits	Declining Profits
Asset Adequacy and Quality (Sale of Low Risk Assets)	Asset Adequacy and Quality (Sale of Low Risk Assets)	Asset Adequacy and Quality (Sale of Low Risk Assets and Less Diversification)
Worsening Macroeconomic Conditions	Worsening Macroeconomic Conditions	Worsening Macroeconomic Conditions
	Increasing Loan Portfolio Risk (especially Industrial Loans)	Increasing Loan Portfolio Risk (especially Consumer Loans)
	Declining Risk-Weighted Capital Ratio (FDIC's insolvency criterion)	Declining Risk-Weighted Capital Ratio (FDIC's insolvency criterion)

Table 5.4. In-Sample Accuracy Classification

	Months prior to failure					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
Classification accuracy (%)	98.59	97.57	96.16	95.21	96.30	95.11
Type I error (%)	10.53	22.11	36.84	44.68	41.11	56.32
Type II error (%)	0.68	0.85	1.19	1.61	0.85	1.10
Pseudo R^2	0.8699	0.7369	0.5878	0.5418	0.5501	0.4756

In a similar fashion, Pseudo R^2 also decreases as the time period model moves farther away from the time of bank failure. The same trend is not observed in the type I and type II error rates. These rates are calculated as percentages of misclassified observations to the total classifications in a certain category (failure versus non-failure). The range for Type I error is from 10.53% in the 6-month time period model to 56.32% in the 48-month time period model.

Type II error rates are considerably smaller, ranging from 0.68% for the 6-month time period model to 1.19% for the 18-month model. For more details on the calculation of these error rates, please refer to Appendix A.

5.1.11 Out-of-Sample Forecasting

It is important to construct a bank failure prediction model that can correctly identify the banks that may fail in the future. Those models, as discussed in chapter 2, are usually referred to as off-site monitoring or early warning model in the literatures and used by bank regulators as a complement to on-site examinations.

In this study, the forecasting efficiency or prediction accuracy of this study's regression results is further tested through out-of-sample forecasting techniques. A separate dataset, consisting of banks that failed in 2010 and 1109 non-failed banks, is compiled for this analysis. The dataset is constructed in the same way that the cross-sectional datasets for the earlier regression were developed.

The estimated coefficients from the previous cross-sectional logistic regression models are used for forecasting or prediction purposes (table 5.1). As before in the in-sample prediction, the cutoff point is set at 0.5 for separating failed and non-failed banks. The results for this out-of-sample forecast are reported in table 5.5.

The out-of-sample classification accuracy ranges from 99.01 to 95.28, reflecting an increasing trend in accuracy rates as the time period models approach the point of bank failure (except for 36 months model, for which the classification error is less than the 24 months). The 48-month model produced the highest rate of type I error (54.08 percent). In contrast, forecasts for the 6-month to 36-month models produced type I error rates that range from 6.93 percent to 41.58 percent.

As before, the type II error rates are much lower than the type I error rates. The range of values for type II error rates are from 0.45% in the 6-month model to 1.53% in the 36-month model. The more detailed derivation of these error rates are presented in Appendix B.

Table 5.5. Out-of-Sample Forecasts

	Months prior to failure					
	6months	**12months**	**18months**	**24months**	**36months**	**48months**
Classification accuracy (%)	99.42	97.44	95.45	95.29	95.95	95.28
Type I error (%)	6.93	17.82	38.61	41.58	32.00	54.08
Type II error (%)	0.45	1.17	1.44	1.35	1.53	1.08

5.2 Stochastic Frontier Analysis (SFA)

Stochastic frontier estimation was applied to calculate the technical efficiency scores for each bank using a panel dataset of 255 banks that failed in 2009-2010 and 1109 surviving banks that passed the filtering criteria previously imposed in the dataset for the prediction model.

5.2.1 Technical Efficiency

A comparative summary of the technical efficiency scores obtained is presented in table 5.5. The summary presents mean technical efficiency scores for each year in the dataset and aggregate measures to draw some comparisons between failed and surviving banks as well as agricultural and non-agricultural banks. The FDIC criterion of categorizing banks as agricultural and non-agricultural is used in this analysis. The FDIC classifies a bank as agricultural if the ratio of its agricultural loans to total loan portfolio exceeds 25%.

Based on the summary in table 5.6, both the surviving and failed banks registered mean technical efficiency scores that are well below 0.50. This implies that in general, banks, regardless of their solvency conditions, have been operating quite inefficiently during the years 2005-2010. It is worth noting that banks that failed in 2009 and 2010 retain their classification as failed banks during the earlier time periods (2005 to 2008) when they were supposed to be still in "favorable financial health." The average technical efficiency score for surviving banks over the 6-year period is 25.59%, while failed banks registered an average 6-year technical efficiency score of only 16.46%. During the entire six-year period, the surviving banks have consistently outperformed failed banks in technical efficiency. These results indicate that the failed banks were actually already not operating efficiently even before the late-2000s recession.

Table 5.6. Technical Efficiency Comparison between Failed banks and Non-failed banks

TE Difference Between Non-failed Banks and Failed Banks				
Bank Characteristics	Mean	Standard Error	Standard Deviation	
Non-failed banks	0.2559	0.0008	0.1269	
Failed banks	0.1646	0.0014	0.0883	
Comparison	Estimate	Standard Error	T value	Pr>|t|
Non-failed banks vs Failed banks	0.0913	0.0016	56.3620	0.0000

Annual breakdown of technical efficiency scores of surviving and failed banks 2005-2010			
Bank Characteristics	Mean	Standard Error	Standard Deviation
2005			
Non-failed banks	0.2533	0.0019	0.1268
Failed banks	0.1626	0.0029	0.0808
2006			
Non-failed banks	0.2544	0.0019	0.1268
Failed banks	0.1620	0.0030	0.0880
2007			
Non-failed banks	0.2555	0.0019	0.1268
Failed banks	0.1641	0.0032	0.0920
2008			
Non-failed banks	0.2566	0.0019	0.1269
Failed banks	0.1650	0.0031	0.0870
2009			
Non-failed banks	0.2576	0.0019	0.1270
Failed banks	0.1721	0.0042	0.0956
2010			
Non-failed banks	0.2586	0.0022	0.1270
Failed banks	0.1642	0.0079	0.0871

Comparison	Estimate	Standard Error	T value	Pr>|t|
2005	0.0907	0.0047	19.4231	0.0000
2006	0.0924	0.0049	20.1498	0.0000
2007	0.0914	0.0046	19.9843	0.0000
2008	0.0916	0.0047	19.5927	0.0000
2009	0.0855	0.0058	14.8719	0.0000
2010	0.0944	0.0116	8.1339	0.0000

The comparison of TE scores for agricultural and non-agricultural banks provides an interesting twist (table 5.7). An important result in this analysis is the fact that successful (or surviving) agricultural banks have been shown to be operating more efficiently than surviving non-agricultural banks. This is important evidence refutes the contention about the relative higher level of riskiness of loans extended to farm borrowers.

Moreover, a comparison of average TE scores for failed agricultural and non-agricultural banks reinforce the earlier result. Not only is the average TE score of failed agricultural banks higher than those of failed non-agricultural banks, but that their average TE even exceeds the average TE score of surviving agricultural banks. While this result could be counter-intuitive, this could be due to the smaller sample of failed agricultural banks as majority of banks with higher agricultural loan portfolios operating during the late 2000s Great Recession have managed to survive the economic crises.

5.2.2 Instrumental Variable Probit Results for the TE Model

The instrumental variable probit (IV Probit) approach was used to determine the role of technical efficiency in bank failure analysis. In the IV Probit model, technical efficiency scores (TE) were estimated by a set of instruments that include all financial variables[4] used in bank failure prediction models. In addition to TE, the probability of bank failure is also determined by two macroeconomic variables, state-level unemployment (UNEMPL) and bankruptcy rates (BF).

[4] Instruments: UNEMRATE, BF, RWCAPRATIO, AGNR, AGR, INDUS, CONSUM, LOANHER, AGTOTAL, CONSTOTAL, INDUSTOTAL, RETOTAL, LIQM1, LIQM2, OVERHEAD, INSIDELN, PROFIT, SIZE, PURCHASEDTL2, DEPLIAB, GAP.

Table 5.7. Technical Efficiency Comparison between Agricultural banks and Non-Agricultural banks

TE Difference Between Ag Banks and Non-Ag Banks				
Bank Characteristics	Observation	Mean	Standard Error	Standard Deviation
Agricultural banks				
Non-failed banks	3427	0.4629	0.0024	0.1379
Failed banks	26	0.7741	0.0530	0.2705
Non-Agricultural banks				
Non-failed banks	22080	0.2238	0.0006	0.0893
Failed banks	3888	0.1605	0.0011	0.0698

Comparison	Estimate	Standard Error	T value	Pr>|t|
Ag-failed vs Ag-non-failed	-0.3111	-.0274	-11.3412	0.0000
Non-Ag failed vs Non-Ag-non-failed	0.0632	0.0015	41.9678	0.0000
Ag-non-failed Vs Non-Ag-non-failed	-0.2392	0.0018	-1.3e+02	0.0000
Ag-failed vs Non-Ag failed	-0.6135	0.1434	-41.7742	0.0000

The original panel dataset was converted to cross-sectional data because of the limitation in IV probit in STATA that does not allow panel data estimation.

Separate regressions were applied to the 2009 and 2010 datasets, which were compiled using the year's last quarter reported by the failed banks (or the quarter prior to the time they were declared insolvent or failed) and the year-end report for surviving, solvent or successful banks.

As reported in table 5.8, the Wald test for exogeneity applied to the IV probit model yields significant Chi-square statistic (χ^2) both for the 2009 and 2010 models, which establishes the endogeneity of the TE variable and reinforces the use of the IVProbit method. The results indicate the strong significance of both macroeconomic variables (unemployment rate and bankruptcy rate) in determining the probability of bank failure. The coefficient results of UNEMRATE and BF suggest that banks located in states with higher rates of unemployment and business bankruptcy rate are more likely to fail. The results for BF are consistent with the results of the previous bank failure prediction models in this study. The consistent performance of UNEMRATE in the 2009 and 2010 models shows its important role in analyzing banks' financial conditions.

The marginal effects reported in table 5.7 also provide us with some important insights. The unemployment rate is an importance determinant of the probability of bank failure, with a 1% increase in unemployment rate increasing the probability of bank failure by 135% in 2009 and 199% in 2010. On the hand, a unit change in the bankruptcy ratio increases the probability of bank failure by 78% in 2009 and 119% in 2010.

The relationship between the probability of bank failure and technical efficiency scores also corresponds to the results of the stochastic frontier analysis. The negative and significant coefficients of TE in both 2009 and 2010 models indicate that banks with lower efficiency scores are more likely to experience insolvency. A 1% increase in technical efficiency scores (TE) will decrease the probability of bank failure by 12% in 2009 and 72% in 2010.

Table 5.8. Results of instrumental variable probit (IVProbit) estimation

	IV Probit			
	2009		2010	
Variables	Coefficient	Marginal effect	Coefficient	Marginal effect
Intercept	-2.2626***		-0.1564	
	(0.2387)		(0.3012)	
A. Instrumented variable				
TE[a]	-2.2172**	-0.1224**	-5.5464***	-0.7264***
	(0.9083)	(0.0460)	(0.8723)	(0.1843)
B. Macroeconomic variables				
UNEMRATE	24.5442***	1.3546***	15.2088***	1.9918***
	(2.0413)	(0.2462)	(1.9907)	(0.2778)
BF	14.1488***	0.7809***	9.1156***	1.1938***
	(2.3740)	(0.1696)	(2.3857)	(0.2484)
Model's Explanatory Power (χ^2)	195.82***		209.56***	
Wald Test of Exogeneity (χ^2)	11.78***		5.63**	

Note:

*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level.
Standard errors are reported in the parentheses.
[a] The instruments used for TE in the IV probit model are UNEMRATE, BF, RWCAPRATIO, AGNR, AGR, INDUS, CONSUM, LOANHER, AGTOTAL, CONSTOTAL, INDUSTOTAL, RETOTAL, LIQM1, LIQM2, OVERHEAD, INSIDELN, PROFIT, SIZE, PURCHASEDTL2, DEPLIAB, GAP.

CHAPTER VI

CONCLUSION AND IMPLICATIONS

"We always overestimate the change that will occur in the next two years and underestimate the change that will occur in the next ten. Don't let yourself be lulled into inaction."
*~ **Bill Gates in "The Road Ahead"***

This study draws upon the predicament of banking institutions during the post 2000s Great Recession when a surge of banking failures was experienced in the last two years of the decade. Reminiscent of the financial crises of the 1980s where the farm sector was easily pinpointed as one of the major sources of the precursors of economic turmoil, this study looks upon the agricultural sector once again to validate if the agricultural sector can once again be labeled as a source of all these economic pandemonium. After all, lenders are naturally inclined to be wary of borrowers from the agricultural sector, given their more significant exposure to sources of risks and uncertainty not usually confronted by businesses from other industries. This study, therefore, addresses the perennial question of whether the riskier, more volatile agricultural sector indeed has contributed significantly in causing and provoking the current crises in the financial industry.

6.1 Early Warning Signals

In addressing this primary goal, this study has developed early warning models that involve a host of potential determinants of the probability of bank failure. These factors include a set of variables representing various facets of the bank's management decisions, operating strategies and financial conditions. In addition to the bank variables, the models also consider the effect of prevailing macroeconomic conditions on the probability of bank failures.

The bank failure prediction models produced results that identified important early warning signals that could be detected as far back as 3 to 4 years prior to a bank's declaration of insolvency or bankruptcy (herein referred to as failure). As early as that time (3 to 4 years from bank failure), the ones that are showing early signs of trouble (or exhibiting trends leading to eventual bank failure) are banks that had to resort to more costly funding arrangements (relying more heavily on more costly sources in the national funds markets), experiencing higher interest rate risk (through the uneven mix of short-term assets and liabilities), registering a downward trend in business profits (if not incurring losses yet), and facing pressure to sell less risky assets to improve liquidity conditions. In addition, deterioration in the general business climate can also affect the likelihood of failure even at this stage.

As the time period approaches the eventual bank failure, increasing trends of delinquencies among industrial/commercial and consumer loans become important early warning signals, in addition to the factors already identified as problem areas in the earlier time period models. True to its use as the FDIC criterion for identifying categories of bank insolvency, the risk weighted capital ratio also becomes an important early warning signal of bank financial distress from the 18-month to the more current or proximate 6-month time period model. This result, however, raises the issue of whether a bank's eventual failure could be averted within 18 months from the incidence of the actual failure, given the results of this research indicating that the FDIC insolvency criterion (risk-weighted capital ratio) can only predict failure as far back as 18 months earlier. In other words, does this result call for an alternative insolvency measure or predictor of eventual insolvency (failure) that can warn of distress much longer than 18 months before the bank plunges into bankruptcy? This matter deserves more special consideration in future research.

The most compelling result in the analyses of early warning signals is the notable insignificance of any measure related to the banks' agricultural loan portfolios. Even agricultural real and non-real estate loan delinquencies have not been established to significantly influence the likelihood of bank failure across all time period models. These results confirm our contention that exposure to a seemingly riskier and more uncertain agribusiness operations does not necessarily enhance a banks' tendency to fail.

The fact that agricultural loans' delinquency rates are consistently below the banks' overall loan delinquency rates also suggests that either agricultural lenders are generally more cautious in making credit decisions or that agricultural borrowers are actually more prudent in the borrowing decisions especially during recessionary times. There is actually evidence that suggest that both of these contentions are valid. During the recessionary period, lenders resorted to adopting policies to tighten the availability of credit in order to prevent the further deterioration of the quality of their loan portfolios. Thus, the lenders' stricter credit risk assessment strategies allow them to lend only to borrowers with loan requests that are adequately secured or those with above average credit ratings. Such credit tightening policies are applied to all borrowers, not just agricultural borrowers.

Moreover, USDA-ERS reports establish the favorable leverage positions of farm businesses all over the country. Farm businesses have been able to maintain very low debt-asset ratios since the 1990s, which have even been declining over certain periods of time. The farm sector also maintains a large percentage of their unused debt repayment capacity that should only validate this study's findings that farm loan delinquency rates are not significant indicators of high probability of bank failure.

Meanwhile, delinquency rates for consumer loans and commercial & industrial loans are significant predictors of bank failure. In a time when consumer credit has become too easy to obtain with the proliferation of credit card offers everywhere, this study's result for this factor is not surprising at all. As commercial/industrial loans are typically larger in magnitude, increases in delinquency in this loan category due to depressed economic demand and diminished economic activity will certainly help lead to bank failure. These results tie in quite nicely with the results of the macroeconomic variables. More pervasive unemployment conditions are indicative of the various industries' struggles to survive and remain viable, which in turn would affect their capability to meet their credit obligations, with such financial woes possibly culminating into eventual bankruptcy for both the indebted businesses and the lending institutions – the commercial banks that closed shop during such difficult times.

6.2 Technical Efficiency

A secondary approach to understanding the determinants of bank failures is through technical efficiency analysis undertaken under the stochastic cost frontier framework. The stochastic frontier analysis allows for the calculation of technical efficiency scores, which are then incorporated in an IV Probit model as an instrumented variable that represents all bank performance variables considered in the bank failure prediction models. The IV Probit model allowed for the evaluation of the TE variable, which has now been a collective (aggregated) measure that captures or represents all bank decisions, strategies, and resulting financial predicament, as a determinant of the probability of bank failure vis-à-vis macroeconomic factors. In other words, the IV Probit allows for the comparison of effects of internal (TE) and external (macroeconomic) factors in affecting the financial health and fate of banks during the most difficult moments of the late 2000s Great Recession.

The results of the IV Probit analysis only emphasize the importance of both internal and external factors in determining the probability of bank failure. As the TE variable is instrumented by a host of financial variables representing various facets of bank business decisions, its significance stress the fact the bank failures are a result of poor business decisions made by bank managers and administrators. However, more than just the internal decision-related factors, the bank's business conditions can be significantly affected by the prevailing macroeconomic conditions. This study's results suggest that when unemployment conditions worsen and more business failures are registered, the general depressing mood in the economy will certainly affect banking businesses to the point that some of them will end up in bankruptcy.

The TE analysis also allows the validation of the relative financial strength of agricultural banks vis-à-vis their non-agricultural counterparts. Results of this analysis confirm that successful agricultural banks have been operating more efficiently than surviving non-agricultural banks. This result only helps refute the contention about the relative higher level of riskiness of loans extended to farm borrowers. The agricultural banks' average TE scores also have been dominant in comparisons between agricultural and non-agricultural failed banks.

6.3 Recommendations for Future Research

Future research may want to consider other possible proxy measures for variables that could potentially also help predict bank failures. For instance, other studies have found management risk, such as the one captured here by insider loan decisions, to be a significant predictor of bank failure. Alternative liquidity measures could also be considered, aside from those already included in this study. Researchers may also want to explore more localized measures of the macroeconomic variables, perhaps at the county level instead of state-level figures, to capture more variability. Alternative formulations for the stochastic frontier framework should also be explored, to evaluate the relative efficiency of the Cobb-Douglas functional form.

Notwithstanding these recommendations, this study has laid out some important foundations in the analysis of causes of the banking crises under the late 2000s Great Recession. This study's bank failure prediction models have identified early warning signals that could offer insights on future banking strategies to employ that should minimize the likelihood of bank failures. More importantly, this study presents an emphatic contention that the agricultural sector, always regarded as a very volatile sector and thus, more likely to be vulnerable to current economic pandemonium, has not significantly ignited the rush of bank failures. After all, the farm sector of today is a far cry from the distressed farm economy of the 1980s. There is no doubt that today's farm sector will certainly endure the economic turbulence of the late 2000s Great Recession.

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APPENDICES

Appendix A. In-sample Classification Accuracy

Six-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
“1”	85	8	93
“0”	10	1172	1182
total	95	1180	1275

Correctly classified: **98.59%** (= (85+1109) / 1210)
Type I error: (prob =1, predicted value = 0) **6.93%** (= 10/95)
Type II error: (Prob = 0, predicted value = 1) **0.45%** (=8/1180)

Twelve-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
“1”	74	10	84
“0”	21	1170	1191
total	95	1180	1275

Correctly classified: **97.57%** (= (74+1170) / 1275)
Type I error: (prob =1, predicted value = 0) **22.11%** (= 21/95)
Type II error: (Prob = 0, predicted value = 1) **0.85%** (=10/1180)

Eighteen-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	60	14	74
"0"	35	1166	1201
total	95	1180	1275

Correctly classified: **95.45%** (= (60 + 1166) / 1180)
Type I error: (prob =1, predicted value = 0) **36.84%** (=35/95)
Type II error: (Prob = 0, predicted value = 1) **1.19%** (=14/1180)

Twenty-Four-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	52	19	71
"0"	42	1161	1203
total	94	1180	1274

Correctly classified: **95.21%** (= (52+1161) / 1274)
Type I error: (prob =1, predicted value = 0) **44.68%** (= 42/94)
Type II error: (Prob = 0, predicted value = 1) **1.61%** (=19/1180)

Thirty-Six-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	53	10	63
"0"	37	1170	1207
total	90	1180	1270

Correctly classified: **96.30%** (= (53+1170) / 1270)
Type I error: (prob =1, predicted value = 0) **41.11%** (=37/90)
Type II error: (Prob = 0, predicted value = 1) **0.85%** (=10/1180)

Forty-Eight-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
“1”	38	13	51
“0”	49	1167	1216
total	87	1180	1267

Correctly classified: **95.11%** (= (38+1167)/1267)

Type I error: (prob =1, predicted value = 0) **56.32%** (=49/87)

Type II error: (Prob = 0, predicted value = 1) **1.10%** (=13/1180)

Appendix B. Out-of-sample Forecasting

Six-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	94	5	99
"0"	7	1104	1111
total	101	1109	1210

Correctly classified: **99.01%** (= (94+1104) / 1210)
Type I error: (prob =1, predicted value = 0) **6.93%** (= 7/101)
Type II error: (Prob = 0, predicted value = 1) **0.45%** (=5/1109)

Twelve-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	83	13	96
"0"	18	1096	1114
total	101	1109	1210

Correctly classified: **97.44%** (= (83+1096) / 1210)
Type I error: (prob =1, predicted value = 0) **17.82%** (= 18/101)
Type II error: (Prob = 0, predicted value = 1) **1.17%** (=13/1109)

Eighteen-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	62	16	78
"0"	39	1093	1132
total	101	1109	1210

Correctly classified: **95.45%** (= (62 + 1093) / 1210)

Type I error: (prob =1, predicted value = 0) **38.61%** (=39/101)
Type II error: (Prob = 0, predicted value = 1) **1.44%** (=16/1109)

Twenty-Four-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	59	15	74
"0"	42	1094	1136
total	101	1109	1210

Correctly classified: **95.29%** (= (59+1094) / 1210)
Type I error: (prob =1, predicted value = 0) **41.58%** (= 42/101)
Type II error: (Prob = 0, predicted value = 1) **1.35%** (=15/1109)

Thirty-Six-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
"1"	68	17	85
"0"	32	1092	1124
total	100	1109	1209

Correctly classified: **95.95%** (= (68+1092) / 1209)
Type I error: (prob =1, predicted value = 0) **32.00%** (=32/100)
Type II error: (Prob = 0, predicted value = 1) **1.53%** (=17/1109)

Forty-Eight-Month Period:

	True		
Classified	Prob = 1	Prob = 0	Total
“1”	53	12	65
“0”	45	1097	1142
total	98	1106	1207

Correctly classified: **95.28%** (= (53+1097)/1106)

Type I error: (prob =1, predicted value = 0) **54.08%** (=53/98)

Type II error: (Prob = 0, predicted value = 1) **1.08%** (=12/1106)