THE RESILIENCE OF AGRICULTURAL LENDERS AND BORROWERS IN THE LATE 2000S FINANCIAL CRISES: APPLICATIONS OF EFFICIENCY, SPLIT-POPULATION DURATION, AND CREDIT RISK MIGRATION MODELS

By

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(Under the Direction of Cesar L. Escalante)

ABSTRACT

This dissertation consists of three essays that feature different approaches in evaluating lender's and borrower's resilience through the late 2000s recession.

The first study applied an Input Distance Stochastic Frontier function to compare estimates of the technical efficiency (TE) and allocative efficiency (AE) between agricultural banks and non-agricultural banks. This efficiency analysis was applied to a seven-year pre-recession period and is designed to identify any early warning signals that could decrease the efficiency level of banks. Results suggest that survival banks were more technically efficient than critically insolvent banks, and banks that tend to utilize cheaper inputs were more likely to withstand the economic crisis.

The second study utilized a split-population survival model in analyzing the role of agricultural loan portfolios on the probability of survival and temporal endurance of commercial bank lenders in the late 2000s recession. The results establish that farm credit transactions neither increased the commercial bank lenders' chances of failure nor expedited the deterioration of their financial conditions. Results indicate that bank failures could have resulted from changes in the quality of the banks' portfolios of real estate, consumer, commercial and industrial loans as well as factors capturing interest rate risk, fund sourcing strategies, and certain structural attributes.

The third study evaluates the credit migration probabilities among different types of farm borrowers from Farm Service Agency (FSA)'s lending program. Two time continuous Markov Chain transition matrices were applied in lieu of the traditional time discrete method, and produced more accurate transition probability estimates that capture the indirect and transient changes in credit risk ratings. Racial and gender minority farmers are found to experience a lower probability of credit rating upgrade than white male farmers. Macroeconomic factors prove to have significant impact on the farms' transition probabilities.

INDEX WORDS: Stochastic Frontier, Input Distance Function, Technical Efficiency, Allocative Efficiency, Survival Analysis, Split-Population Duration Analysis, Credit Risk Migration, Cohort Method, Markov Chain, Ordered Logistic Regression

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A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2015

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DEDICATION

Dedicated to my beloved wife, Shengfei Fu, and my dear son, Boyang (Lucas) Li, my parents, Fanying Zeng and Hong Li, for their love and support

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my major advisor, Dr. Cesar L. Escalante, for his invaluable guidance and support through my 6 years of study. I am privileged and honored to have him as my advisor. His wisdom, patience as well as his full support, genuine concern and care he has demonstrated toward my personal and professional development have been a priceless experience for me at The University of Georgia.

My sincere gratitude also goes to Dr. Karali and Dr. Brewer, who served as my committee members. I would like to express my appreciation to them for commenting on my dissertation and providing me with research advice.

I would like to thank Dr. Epperson and Dr. Gunter for guiding me through my first academic paper when I was working on my master degree. They were very knowledgeable, generous, enthusiastic, and have always been available to advise me.

My heartfelt thanks to all the faculties and staffs from Department of Agricultural and Applied Economics. Their kind help and support are always appreciated.

I could never have achieved my PhD degree without the support of my colleagues and friends in this department. I will never forget the moment we shared together: preparing together for qualify exams, working side-by-side in the graduate lab, and holding birthday party for each other.

Last, but not least, my deepest gratitude and love goes to my wife, Shengfei Fu, my parents, Fanying Zeng and Hong Li, and my dearest son, Boyang Li. Their unconditional love and support helped me through all kinds of obstacles.

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

Introduction

1.1 Background

In the United States, agriculture is a capital intensive industry that requires medium- to long-term investments in farmland, machinery, and equipment while working capital funds are constantly needed to sustain production cycles in the short-run. The survival and growth of farm businesses can be hindered by a capital constraint, among many other major obstacles. Finance theory suggests a pecking order model of capital sourcing, which was developed by Myers (1984) and Myers and Majluf (1984). This made proposes a hierarchical ordering of sources of capital based on adverse selection issues that arise when a firm has more information about its value than the providers of funds. According to such a prioritization scheme, internally generated funds are usually first in the hierarchy. When such funding sources are depleted, the firm resorts to external borrowing (debt). Raising equity capital is considered as the last funding resort. Modigliani and Miller have long argued, since their seminal work in 1958, that external debt can increase a firm's value, unless the composite effects of taxation and bankruptcy will require regulation of capital structure decisions towards an optimum.

The role of external debt in the viability, survival, and expansion of the farm industry can therefore not be understated. The financing supplied by banks and other lenders over the years has been essential to individual farm businesses as well as to the entire industry. Commercial banks today play a significant role in providing financial assistance to farm businesses and other agribusiness-related activities. Interestingly, being a farm credit provider has not been an original intention of commercial banks. Initially, the commercial banking system was established primarily to support merchants and manufacturers. However, the reduction in minimum capital-stock requirements and tax on note circulation in 1900 made it possible to establish national banks in smaller towns that paved the way for the accommodation of the credit requirements of isolated farming communities (Lee, 1930). Nowadays, commercial banks are a primary supplier of credit to small and mid-size farms and are the leading source of non-real estate farm loans and also rank high in providing farm real estate loans.

However, the lender-borrower relationship between commercial banks (as well as other farm lenders) and their farm borrowing clientele may be strained during periods of high economic volatility and distress. The 1980s farm crisis, for instance, resulted in thousands of bank failures after credit decisions were prematurely based on temporary appreciation in farmland values[1]. The lessons learned from such an unfortunate episode, however, required a more careful assessment of agricultural risks and the adoption of more cautious, prudent lending and borrowing decisions.

Recently, the economy was hit by another major economic shock. By the end of 2007, the burst of the housing bubble in the U.S has led to the worst economic crisis experienced locally and globally since the Great Depression of 1930s. Investment in subprime residential mortgage-backed securities (RMBS) has been singled out as having triggered this financial crisis. A dramatic increase in delinquencies in subprime residential loan accommodations due to the housing boom-and-bust in the second half of 2006 caused the default of hundreds of thousands of borrowers within a short period of time. As a result, major banks in U.S. and Europe began to struggle to

[1] FDIC "History of the 80s: Chapter 8, Banking and the Agricultural problems of the 1980s". https://www.fdic.gov/bank/historical/history/vol1.html

remain viable after heavily investing in subprime mortgages for a decade and a half. Then the crisis eventually spread globally.

In residential real estate loan transactions prior to the recession, speculative borrowing easily tolerated subprime mortgage transactions. The economic environment allowed for easy access to credit as interest rate stayed low and foreign funds were pouring into the economy. These conditions produced a housing market boom as real estate prices rose dramatically from 2002 onwards. The housing bubble would, however, burst in late 2006. As a result, inflationary and tight market conditions brought about hundreds of thousands of loan defaults and the default rate constantly grew in a short period of time. In the U.S., the crisis affected other industries. The banking industry was severely affected that nearly 500 banks failed from 2007 until the end of 2013. During this time, the number of critically insolvent banks included in the "High Risk of Failing Watch List" maintained by Federal Deposit Insurance Corporation (FDIC) also increased dramatically.

1.2 Major Study Goals

Drawing from the lessons of the 1980s farm crisis, this study will evaluate the resilience of the farm sector through the more recent financial crisis. This study will analyze farm economic resilience from two perspectives: the lenders' and the farm borrowers' perspectives. On one hand, the survival strategies of agricultural lenders in the commercial banking industry will be analyzed vis-à-vis the less specialized non-agricultural banks. On the other hand, changes in farm borrower quality will be assessed by tracking down the financial performance of existing direct farm loan clients of the Farm Service Agency from the pre-recession through the post-recession years. The following sub-sections will provide further background on these specific objectives.

1.2.1 Agricultural Banks' Survival Strategies

The specialized lending operations of agricultural banks result in certain inherent structural and operating attributes. Compared to regular commercial banks, agricultural banks usually have more liquidity concerns. One third of all agricultural debts are held by rural banks with assets of less than $50 million. Hence, agricultural banks are unable to diversify their clientele to include other non-agricultural business clientele due to funding constraints. The specialized nature of their lending operations and large variability of the agricultural products' price usually result in greater risk and uncertainty. Back in 1980s, the escalating value of farm real estate has resulted in a large number of investments in farm real estate. In order to take an advantage of this opportunity, farmers assumed a substantial amount of debt. However, interest rates skyrocketed in early 1980s coupled with a sharp decline in the foreign demand for domestic agricultural products. Consequently, real farm incomes and farm real estate values both dropped rapidly. This resulted in numerous agricultural bank failures that further increased dramatically in the mid-1980s.

As the economy was dealt another major recession, analysts are wary that the farm sector could easily succumb to the pressure given the economic vulnerability it showed in other recessionary periods. The concern was that whether the farm lending industry would again be adversely affected just like it had been during the 1980s farm financial crisis. There were telltale signs during the recession as grain prices dropped by almost 50% from July to October of 2008 (Boehlje and Hurt, 2009). More concerns were raised towards financing agricultural investment. Even though agricultural loans have maintained a delinquency rate lower than other loan types and far below the agricultural delinquency rates exhibited during the financial crisis in mid-1980s, bankers still boosted the risk rating and collateral requirements on agricultural loans after observing a slight increase in delinquency rates from 2008 to 2009.

The profitability of banks that lend heavily to agriculture actually improved by the end of 2010, with an average rate of return on assets (ROA) of 0.88% that exceeds the average (0.64%) for all commercial banks (Ellinger, 2011). Only 134 failed commercial banks out of 205 commercial bank failures from 2009 to 2010 held some agricultural loans, although these banks can hardly be considered as specialized agricultural banks given their agricultural loan portfolios constitute only about 2.09% of their total portfolios (Ellinger, 2010).

The farm lenders in the commercial banking industry registered contrasting performance records during the 1980s and later 2000s recessionary periods. Given such contrast, this study is an attempt to discern the underlying operating and business strategies employed by agricultural banks during the latest recession. This study will shed light on certain decisions made by such specialized banks that allowed them to avoid duplication of the 1980s farm financial crisis and manage to fare well during the recent recession while their peers were struggling.

1.2.2 Recessionary Effects on Changes in the Quality of Farm Borrowers

During recessionary periods, many farm businesses may be plagued with increased volatility in commodity prices, dwindling market supplies of much needed inputs, diminishing aggressiveness in consumer purchase decisions, and relatively tighter credit conditions. Some businesses may be forced to downsize, if not completely close down their operations, as their viability potentials are seriously compromised.

This study examines any significant changes in farm businesses' financial conditions during the latest recessionary period. The Farm Service Agency (FSA) under the United States Department of Agriculture (USDA) has made available a dataset of farm borrowers and their financial performance indicators spanning through the years before, during, and after the last recession. The FSA borrower dataset can be considered as ideal for this study's interest in borrower quality changes during times of hardship.

The FSA, being the government's lending arm to farmers, implements loan programs guided by the government's mission to assist underserved sectors of the farm economy experiencing difficulty in gaining access to borrowed funds through commercial lending channels (Escalante et al, 2006). Clients include farm businesses whose loan applications have been previously turned down by regular lenders. This alone earns the FSA the label "lender of last resort." Its philosophy is that borrowers that were turned down because of lack of track record or credit history as well as entrepreneurs with business potential and promise who are starting new businesses need to be given a boost to prove their business skills and creditworthiness. Its commitment to equitable dispensation of credit pushes FSA to target socially and financially disadvantaged farmers – such as racial and gender minority groups, limited resource farmers, beginning farmers, and other small farm businesses.

The FSA has two major loan programs that actually represent steps in a ladder toward borrower financial independence and maturity. The first program is the direct loans program that is made available to farm borrowers under the underserved borrower categories earlier discussed. The original intent of FSA is to guide the direct loan borrowers toward some maturity and allow them to graduate to the guaranteed loan program, the second program in the hierarchy. Under the guaranteed loan program, the borrower can now borrow from a regular lender, with FSA at the backdrop as a guarantor of the farmers' loans. Needless to say, FSA guarantees enhance a farm borrower's chances of availing of regular credit from farm lenders. The ultimate goal is for the borrower to eventually transition to a more mature borrower that can independently obtain loans from a regular lender, without any assistance from the FSA.

Thus, this study's analysis of FSA's direct loan clients fits well with the original design to analyze borrowers' vulnerability to or resilience under periods of significant economic stress. This study is expected to produce important implications on how certain farm business categories, such as those operated by minority and financially disadvantaged farmers, can survive difficult challenges in their businesses. The FSA also stands to benefit from this study by deriving important insights on how to improve their direct loan program to better assist their clients.

1.3 Objectives

The goals of this dissertation research will be addressed in three essays that feature different approaches in evaluating lenders' and borrowers' resilience through the last recession. The first two essays are from the lenders' perspective providing accounts of the lenders' strategies for survival while the third essay examines the quality of FSA direct loan borrowers. The following subsections provide an overview of the analytical techniques and empirical design employed in each individual study or essay.

1.3.1 Technical and Allocative Efficiencies of Agricultural and Non-Agricultural Banks

The first essay applies the Input Distance Stochastic Frontier Function to estimate the technical efficiency (TE) and allocative efficiency (AE) of several categories of commercial banks operating during the pre-recession era. A panel dataset of U.S. commercial banks is compiled that captures pre-recession conditions (backtracking to four years and earlier prior to the surge of bank failures in 2009 and 2010).

In this study, the banks' input-allocation decisions are scrutinized to identify over-utilized and underutilized operating inputs and determine cost savings that would have been realized if banks deviated from actual non-optimal input allocation decisions. This analysis involves a more in-depth scrutiny of input trade-off decisions and cost-saving implications that go beyond a mere validation of bank failure predictors. The analyses are designed to identify notable distinctions in pre-recession operating decisions and resulting efficiencies among such banking categories: a) between the more specialized, smaller agricultural banks and the more diversified, larger non-agricultural banks; and b) between non-agricultural banks that eventually failed and those agricultural banks that survived the banking crises. The first level of distinction allows for the identification of input allocation and other operating decisions that enhanced the probability of eventual bank survival. The second layer of the analyses evaluates the effects of industry specialization on agricultural banks' resiliency to withstand the obstacles to survival under recession.

1.3.2 Split-Population Survival Model for Commercial Banks

Predicting the default risk for banks, loans and securities has been a constant concern of regulating authorities, prospective investors, analysts and other players in the finance industry (Demyanyk and Hasan, 2010). In fact, most central banks have employed various Early Warning Systems (EWS) to monitor the riskiness of their banking constituents. However, the repeated occurrence of banking crises indicates that safeguarding the banking system is not an easy task.

This study is designed to identify signals of failures for commercial banks as well as pinpoint factors that could enhance the survival ability of agricultural and non-agricultural banks. Specifically, this study analyzes the financial behavior of agricultural banks relative to their non-agricultural banking counterparts to shed light on their survival strategies during the recent financial crisis and determine how such strategies differ from those employed by surviving non-agricultural banks.

Most empirical work in this area have used logistic regression techniques to predict bank failure. This analysis differentiates itself from previous early warning model studies by using a special type of duration model called a Split-Population Duration Model. Previous studies (Schmidt and Witte 1989, Cole and Gunter 1995, Deyoung 2003) have emphasized the split-population duration model's strength in addressing two shortcomings of the basic duration model (including the Cox model): first, the basic model assumes that every bank would eventually fail as risk is magnified through time; second, the likelihood function fails to distinguish between the determinants of failure and the factors influencing the timing of failure (Cole and Gunter 1995). The split-population model instead accounts for the heterogeneity of experiences, which acknowledges the fact that some observations in the sample will never experience the event of interest while the others do.

1.3.3 Credit Risk Migration of FSA's Direct Loan Borrowers

The third study analyzes the effect of recessionary conditions on the quality of farm borrowers under a credit risk migration framework. This study is covered by a Memorandum of Agreement (MOA) with the Farm Service Agency (FSA) of the U.S. Department of Agriculture (USDA) that provides this research project access to an extensive national database of existing FSA borrowers and their financial records.

The analysis will be undertaken in two phases. First, two Markov chain time approaches, time homogenous and non-homogenous models, will be used to determine farm credit risk migration rates. These models capture indirect, transient changes in farm credit risk ratings that are usually omitted under the traditional time discrete cohort method. The results of these two methods are then compared against result under the cohort method. This analysis expects to obtain more accurate, reliable credit risk transition and portfolio stress/default probability rates under the Markov chain models.

In the second phase of the analysis, demographic, structural, macroeconomic and other financial factors will be evaluated to determine their influence on the movement of farm borrowers' credit migration: upgrade, retention, and downgrade. This segment of the analysis will provide important, useful information, especially to FSA as results could provide insights that may lead to some modifications in their program policies or operating procedures to better assist their underserved borrowing clientele.

1.4 Organization

This dissertation is comprised of five chapters. Chapter 1 provides an overview and background of the entire scope and general theme of this dissertation research. Chapter 2 presents the stochastic frontier analysis of efficiencies and input allocation decisions of banks during the pre-recession period. Chapter 3 presents the split population duration study that identifies survival strategies of agricultural and non-agricultural banks during the recessionary period. Chapter 4 discusses the credit migration study that tracks changes in the quality of farm borrowers of the Farm Service Agency in the pre- and post-recession periods. Chapter 5 summarizes all the results of the three studies and discusses recommendation for further research.

CHAPTER 2

Pre-Recession Efficiencies and Input Allocation Decisions of Successful, Critically Insolvent and Specialized Banks of the Late 2000s Financial Crises

2.1 Introduction

The late 2000s economic recession that affected both the U.S. and global economies is considered the longest economic downturn since the 1930s Great Depression (NBER, 2010). The U.S. economy was plagued by high unemployment, bankruptcies and foreclosures, among other setbacks when housing prices started dropping significantly in 2006, after posting record high levels in the early 2000s. Declining real estate values ignited an increase in loan defaults and mortgage foreclosures that led to a surge of bank failures at an alarming rate not experienced by the U.S. banking industry since the 1980s.

Specifically, subprime residential loan delinquencies were rampant in the ensuing financial crises in 2007 (Demyanyk and Hasan, 2010). In residential real estate loan transactions prior to the recession, speculative borrowing easily tolerated subprime mortgage transactions. The economic environment allowed for easy access to credit as interest rates were low and foreign funds were pouring into the economy. These conditions produced a housing market boom as real estate prices rose dramatically since 2002. This housing bubble would, however, burst in late 2006. As a result, inflationary and tight market conditions brought about hundreds of thousands of loan defaults and the default rate constantly grew in a short period of time.

A total of 509 bank failures were recorded by the Federal Deposit Insurance Corporation (FDIC) from January 2007 to December 2014, with nearly 60% of these failures occurring in 2009 and 2010. In contrast, there were only 24 bank failures in the U.S. during the seven-year period prior to 2007 (FDIC, 2015). In addition to the banks that actually failed in recent years, the FDIC has also maintained a watch list of banks that are operating under some stress as determined by FDIC's set of critical financial performance indicators. By the end of 2014, around 290 banks received either "poor" or "very poor" ratings using such standards, and, hence, these banks were closely monitored by FDIC (Liu, 2014).

A number of empirical works in corporate finance literature have examined the determinants of bank failures from previous episodes of financial crises. These studies analyzed the nature and consequences of management decisions (Belongia and Gilbert, 1990), the effect of insider loans (Graham and Horner, 1988; Seballos and Thomson, 1990; Belongia and Gilbert, 1990; Thomson, 1991), the impact of overhead costs (Demirguc-Kunt, Laeven, and Levine, 2003; Seballos and Thomson, 1990; Thomson, 1991), the effects of product diversification and industry concentration on bank performance (Thomson, 1991; DeYoung and Hasan, 1998), and the impact of audit quality on bank failure (Jin, Kanagaretnam, and Lobo, 2011). Different bankruptcy prediction models have widely used the basic probit/logit model as their analytical tool (Cole and Gunther, 1998; Hanweck, 1977; Martin, 1977; Pantalone and Platt, 1987; Thomson, 1991).

A more recent study dealing with the late 2000s recession developed an early warning model in a logistic regression framework that considers factors that can predict the eventual occurrence of bank failures (Li et al., 2013). The study's bank failure warning or predictor variables include measures of adequacy and asset quality, management risk, liquidity risk, bank earnings potential, loan portfolio composition and risk, funding arrangements, structural factors, and macroeconomic indicators. The study analyzed several time period models defined at specific historical time points away from the actual occurrence of bank failure. An interesting result of this study contends that bank failures can be predicted as early as three to four years prior to the actual event through crucial operating decisions affecting funding arrangements, interest rate risk, and asset quality and adequacy, among others.

This analysis revisits and validates these contentions by scrutinizing certain components of operating decisions made by banks that either survived or became critically insolvent during the late 2000s financial crises. The study period backtracks to two years and earlier prior to the surge of bank failures in 2009 and 2010. This analysis employs the Translog input distance function under a stochastic frontier analysis framework to evaluate the technical and allocative efficiencies of the sample banks. The banks' input allocation decisions are scrutinized to identify over-utilized and under-utilized operating inputs to determine input trade-off decisions based on cost considerations, instead of merely validating bank failure predictors identified in the previous study (Li et al., 2013).

This study also presents a comparative analysis of the cost efficiency and input allocation decisions of more specialized agricultural banks vis-à-vis their less non-agricultural banking peers operating during the sample period. Compared to regular commercial banks, agricultural banks usually have more liquidity concerns. One third of all agricultural debts are held by rural banks with assets of less than $50 million. Thus, agricultural banks are unable to diversify their clientele to include other non-agricultural business clientele due to funding constraints. The specialized nature of their lending operations and the large variability of the agricultural products' prices usually result in greater risks and uncertainty. However, despite such constraints and concerns, studies and statistics show that agricultural banks actually fared relatively better than their non-agricultural peers throughout the latest recessionary period. Interestingly, the farm lending sector, which accounts for 30.1% of the number of banks operating in the U.S. banking industry, only experienced 27 bank failures since 2007 (ABA, 2012). This figure is only 5.5% of the total bank failures registered during the period 2007 to early 2013. Moreover, delinquency rates for agricultural loans have been consistently one of the lowest among several loan categories in commercial banks during the recessionary period (Kauffman and Akers, 2013).

The eventual failure of critically insolvent non-agricultural banks and the relative success of most specialized agricultural banks during the last recession will provide an interesting contrast of operating decisions and strategies. Specifically, this study will shed light on these banks' efficiency and input allocation decisions to discern their strategies for operating more prudently and thriving through the recession.

2.2 Theoretical Framework

This section presents a discussion of the theoretical foundation of this study. The discussion begins with a layout of the economic efficiency framework that provides an understanding of a firm's operating environment, goals and constraints. Then, the firm's owner's motivations for making input allocation decisions are analyzed that require controlling or monitoring the use of certain production inputs vis-à-vis other inputs.

2.2.1 The Technical Efficiency Model

In developing the efficiency analysis model under the stochastic frontier framework, a generic form of the input distance function is first defined as follows (Shephard, 1953):

$$D^I(\mathbf{x},\mathbf{y}) = \sup_{\rho}\{\rho > 0 : (\mathbf{x}/\rho) \in L(\mathbf{y})\} \tag{2.1}$$

where the superscript I implies that it is the input distance function; the input set $L(\mathbf{y}) = \{\mathbf{x} \in \mathbf{R}_N^+ : \mathbf{x} \text{ can produce } \mathbf{y} \in \mathbf{R}_\mathbf{M}^+\}$ represents the set of all input vectors, $\mathbf{x}$, that can produce the output vector, $\mathbf{y}$; and ρ measures the possible proportion of the inputs that can be reduced to produce the quantity of outputs not less than $\mathbf{y}$. In other words, the input distance function determines the maximum proportion of retraction in input levels to achieve the output levels defined along the production frontier.

The stochastic frontier analysis (SFA) approach is introduced to estimate the flexible Translog distance function. Distance functions can be used to estimate the characteristics of multiple output production technologies in the absence of price information and whenever the cost minimization or revenue maximization assumptions are inappropriate. This analytical framework applies well to banking operations. Banking operations are often characterized by multi-outputs and multi-inputs. Moreover, banks usually have greater grasp or control over operating inputs instead of their outputs.

This analysis adopts the Translog function that overcomes the shortcomings of the usual Cobb-Douglas function form, which assumes that all firms have the same production elasticities. The Translog function is more flexible with less restriction on production and substitution elasticities. The flexibility reduces the possibility of producing biased estimates due to erroneous assumption on the functional form.

Hence, the stochastic input distance function for each observation *i* can be estimated by:

(2.2)
$$\begin{aligned}\ln D_{it}^{I} &= \beta_0 + \sum_{k=1}^{M}\beta_{y_k}\ln y_{k,it} + \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M}\beta_{y_{kl}}\ln y_{k,it}\ln y_{l,it} + \sum_{j=1}^{N}\beta_{x_j}\ln x_{j,it} + \frac{1}{2}\sum_{j=1}^{N}\sum_{h=1}^{N}\beta_{x_{jh}}\ln x_{j,it}\ln x_{h,it} \\ &+ \sum_{j=1}^{N}\sum_{k=1}^{M}\beta_{xy_{jk}}\ln x_{j,it}\ln y_{k,it} + \sum_{d=1}^{P}\beta_{z_d}\ln z_{d,it} + \frac{1}{2}\sum_{d=1}^{P}\sum_{f=1}^{P}\beta_{z_{df}}\ln z_{d,it}\ln z_{f,it} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ln y_{k,it}\ln z_{d,it} \\ &+ \sum_{j=1}^{N}\sum_{d=1}^{P}\beta_{xz_{jd}}\ln x_{j,it}\ln z_{d,it} + \sum_{k=1}^{M}\alpha_k(t\ln y_{k,it}) + \sum_{j=1}^{N}\delta_j(t\ln x_{j,it}) + \sum_{d=1}^{P}\theta_d(t\ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\ &+ d_a dum_{a,it}\end{aligned}$$

where $dum_{a,it}$ is the dummy variable for agricultural banks; *k*, *l* = 1, … *M* and *M* = 5 (number of outputs); *j*, *h* = 1, … *N* and *N* = 4 (number of inputs); *d*, *f* = 1, … *P* and *P* = 2 (number of indexes to measure financial risks and loan's quality).

A necessary property of the input distance function is homogeneity of degree one in input quantities, which required the parameters in equation (2.2) to satisfy the following constraints:

(R1) $$\sum_{j=1}^{N}\beta_{x_j} = 1$$

(R2) $$\sum_{j=1}^{N}\beta_{x_{jh}} = 0, \qquad \forall\ h = 1,\ldots,N$$

(R3) $$\sum_{j=1}^{N}\beta_{xy_{jk}} = 0, \qquad \forall\ k = 1,\ldots,M$$

(R4) $$\sum_{j=1}^{N}\beta_{xz_{jd}} = 0, \qquad \forall\ d = 1,\ldots,P$$

(R5) $$\sum_{j=1}^{N}\delta_j = 0\cdot$$

In addition, the property of homogeneity can be expressed mathematically as:

(2.3) $$D_{it}^{I}(\lambda\mathbf{x},\mathbf{y}) = \lambda D_{it}^{I}(\mathbf{x},\mathbf{y}), \qquad \forall\lambda > 0\,.$$

Assuming that $\lambda = 1/x_{N,it}$ [2], equation (2.3) can be expressed in the logarithmic form as:

---

[2] λ is selected as arbitrary input to serve as the denominator considering the input distance function's property of homogeneity of degree one in inputs (here the N^{th} input is selected as the denominator).

(2.4) $$\ln D_{it}^{I}(\mathbf{x}/x_{N,it},\mathbf{y}) = \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) - \ln x_{N,it}\,.$$

According to the definition of the input distance function, the logarithm of the distance function in (2.4) measures the deviation (ε_{it}) of each observation $(\mathbf{x},\mathbf{y})$ from the efficient production frontier $L(\mathbf{y})$:

(2.5) $$\ln D_{it}^{I}(\mathbf{x},\mathbf{y}) = \varepsilon_{it}\;.$$

Such deviation from the production frontier (ε_{it}) can be decomposed as $\varepsilon_{it} = v_{it} - u_{it}$. Thus, equation (5) can be rewritten as:

(2.6) $$\ln D_{it}^{I}(\mathbf{x},\mathbf{y}) = u_{it} - v_{it}$$

where u_{it} measures the technical inefficiency that follows the positive half normal distribution as $u_{it} \overset{iid}{\sim} N^{+}(\mu,\sigma_u{}^2)$ while v_{it} measures the normally distributed pure random error $v_{it} \overset{iid}{\sim} N(0,\sigma_v{}^2)$.

Substituting equation (2.6) into equation (2.4), equation (2.4) can then be rewritten as:

(2.7) $$-\ln x_{N,it} = \ln D_{it}^{I}(\mathbf{x}/x_{N,it},\mathbf{y}) + v_{it} - u_{it}\;\;.$$

Aside from the homogeneity restrictions, symmetric restrictions also need to be imposed in estimating the Translog input distance function. The symmetric restrictions require the parameters in equation (2.2) to satisfy the following constraints:

(R6) $$\beta_{y_{kl}} = \beta_{y_{lk}}\,,\ \text{where}\quad k,l = 1,....,M$$

(R7) $$\beta_{x_{jh}} = \beta_{x_{hj}}\,,\ \text{where}\quad j,h = 1,....,N$$

(R8) $$\beta_{z_{df}} = \beta_{z_{fd}}\,,\ \text{where}\quad \mathrm{d},\,f = 1,....,P\;\;.$$

Imposing restrictions (R1) to (R8) on equations (2.2) and (2.7) yields the following estimating form of the input distance function:

(2.8)

$$
\begin{aligned}
-\ln x_{N,it} = \beta_0 &+ \sum_{k=1}^{M}\beta_{y_k}\ln y_{k,it} + \sum_{j=1}^{N-1}\beta_{x_j}\ln x_{j,it}{}^{*} + \sum_{d=1}^{P}\beta_{z_d}\ln z_{d,it} \\
&+ \frac{1}{2}\left[\sum_{k=1}^{M}\beta_{y_{kk}}(\ln y_{k,it})^2 + \sum_{j=1}^{N-1}\beta_{x_{jj}}(\ln x_{j,it})^2 + \sum_{d=1}^{P}\beta_{z_{dd}}(\ln z_{d,it})^2\right] \\
&+ \sum_{k=1}^{M}\sum_{l=1,\ for\ l>k}^{M}\beta_{y_{kl}}\ln y_{k,it}\ln y_{l,it} + \sum_{j=1}^{N}\sum_{h=1,\ for\ h>j}^{N-1}\beta_{x_{jh}}\ln x_{j,it}{}^{*}\ln x_{h,it}{}^{*} + \sum_{d=1}^{P}\sum_{f=1,\ for\ f>d}^{P}\beta_{z_{df}}\ln z_{d,it}\ln z_{f,it} \\
&+ \sum_{j=1}^{N-1}\sum_{k=1}^{M}\beta_{xy_{jk}}\ln x_{j,it}{}^{*}\ln y_{k,it} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ln y_{k,it}\ln z_{d,it} + \sum_{j=1}^{N-1}\sum_{d=1}^{P}\beta_{xz_{jd}}\ln x_{j,it}{}^{*}\ln z_{d,it} \\
&+ \sum_{k=1}^{M}\alpha_k(t\ln y_{k,it}) + \sum_{j=1}^{N-1}\delta_j(t\ln x_{j,it}{}^{*}) + \sum_{d=1}^{P}\theta_d(t\ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
&+ d_a dum_{a,it} + v_{it} - u_{it}
\end{aligned}
$$

where $x_{j,it}{}^{*} = x_{j,it}/x_{N,it}$ is the normalized input *j*. This estimating equation will be applied to a general model using all bank observations and two disaggregated models for agricultural and non-agricultural banks to determine any deviant variable effects that may be attributed to more specialized banking operations.

Since our model is estimated for panel data, the hypothesis of time-invariance ($\eta = 0$) needs to be tested. For the general model form, the inefficiency effects can be modeled as

(2.9) $$u_{it} = \exp\{-\eta(t - T_i)\}.u_i$$

where $u_i \overset{iid}{\sim} N^{+}(\mu, \sigma_{\mu}^{2})$. If $\eta = 0,$ then the time-invariance hypothesis cannot be rejected and the model becomes a time-invariant model. If the hypothesis is rejected, then a time variant model results and time-variant constraint ($\eta \neq 0$) will be imposed in estimating equation (2.8). Additionally, the sign of the η can indicate the nature of the change in efficiency across the time series. A positive sign means an achievement of efficiency, while a negative sign indicates deterioration in efficiency. After estimating all coefficients in equation (2.8), the coefficients for the N^{th} input can be calculated by imposing the homothetic restrictions (R1) to (R5).

2.2.2 Input Allocation Efficiency

Moreover, efficiency can be decomposed into two separate components: technical efficiency (TA) and allocative efficiency (AE). Unfortunately, as Bauer (1990) has pointed out, it is difficult to obtain separate TE and AE measures. Figure 2.1 will help understand the mechanics of such decomposition. In the plots, assume a firm that uses two inputs (x1 and x2) to produce the output *y*. Technical inefficiency would occur at point A since it is possible that the same amount of output could be produced with fewer inputs by a movement from point A to point C. The percentage of input savings that will result from that movement is actually the TE measure calculated as $TE = OC / OA$ (actual production/optimal production). Recalling the definition of the input distance function, the following linkage can be established between $D^I(\mathbf{x}, \mathbf{y})$ and *TE*.

(2.10) $$TE = 1 / D^I(\mathbf{x}, \mathbf{y}) .$$

Given the input prices p_1 and p_2, the AE concept can also be illustrated in Figure 2.1. The move from C to D in the isoquantity curve shows that the firm's output has been maintained at the same level even while operating at a lower isocost curve *f1*. This implies that the firm could realize cost savings even without incurring any decrease in output production. The cost savings can be represented by AE that can be calculated as $AE = OB / OC$.

The estimated input distance function will be used to further differentiate technical and allocative efficiencies. TE levels can be calculated by

(2.11) $$TE_{it} = 1 / D_{it}^I = 1 / E[\exp(u_{it}) \,|\, v_{it} - u_{it}]$$

where $0 \le TE_{it} \le 1$. The closer TE_{it} is to unity, the more technically efficient a company is. Considering the panel data nature of this analysis, u_{it} can be expressed as equation:

(2.12) $$u_{it} = \exp\{-\eta(t - T_i)\}u_i.$$

$\eta = 0$ implies that the distance function is time invariant and, hence, will not fluctuate throughout the time series; otherwise, the model is time-variant.

Allocative efficiency can be assessed by estimating the inputs' shadow prices. Earlier studies on allocative efficiency were based on the estimation of a system of equations composed of the cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, this approach requires imposing the condition of cost minimization. Recent studies have shown an alternative method for obtaining input shadow prices using Shephard's distance function (Fare and Grosskopf, 1990; Banos-Pino, Fernández-Blanco, and Rodríguez-Álvarez, 2002; Atkinson and Primont, 2002; Rodríguez-Álvarez, Fernández-Blanco, and Lovell, 2004). This new approach no longer requires the cost minimization condition to produce consistent estimates. This method analyses differences between the market and shadow prices with respect to the minimum costs.

Recalling the plots in Figure 2.1, the shadow price ratio p_1^s / p_2^s is the slope of the isocost curve *f3*, which indicates the minimum cost of production at a given levels of inputs to produce the same output quantity. In other words, a firm would be allocative efficient if it operates at point C, which is on the isocost curve *f3* to satisfy the condition required by allocative efficiency. This condition requires that the marginal rate of technical substitution (MRTS) between any two of its inputs is equal to the ratio of the corresponding input prices (p_1^s / p_2^s). So the deviation of the market price ratio (p_1 / p_2) from the shadow price ratio (p_1^s / p_2^s) reflects allocative inefficiency.

The price ratio can be expressed as $k_{12} = \frac{p_1^s / p_2^s}{p_1 / p_2}$. Specifically, if the ratio equals to 1, allocative efficiency is achieved.

In general, the allocative inefficiency for each observation *i* at time *t* can be measured by the relative input price correction indices (herein also referred to as the input allocation ratio):

(2.13)
$$k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p_{j,it}{}^s / p_{j,it}}{p_{h,it}{}^s / p_{h,it}} = \frac{p_{j,it}{}^s}{p_{h,it}{}^s} \cdot \frac{p_{h,it}}{p_{j,it}}$$

where $k_{j,it} = p_{j,it}{}^s / p_{j,it}$ is the ratio of the shadow price, $p_{j,it}{}^s$, to the market price, $p_{j,it}$, for input *j* of firm *i* at time *t*. If $k_{jh,it} = 1$, allocative efficiency is achieved. If $k_{jh,it} > 1$, input *j* is being underutilized relative to input *h*. If $k_{jh,it} < 1$, input *j* is being over-utilized relative to input *h*.

Atkinson and Primont (2002) derived the shadow cost function from a shadow distance system. In the shadow distance system, the cost function can be expressed as:

(2.14)
$$C(\mathbf{y}, \mathbf{p}) = \min_{\mathbf{x}} \{\mathbf{px} : D(\mathbf{y}, \mathbf{x}) \geq 1\}.$$

Implementing the duality theory and imposing input distance function's linear homogeneity property, the study demonstrated that the dual Shephard's lemma can be derived as:

(2.15)
$$\frac{\partial D_{it}^I(\mathbf{x}, \mathbf{y})}{\partial x_{j,it}} = \frac{p_{j,it}^s}{C(\mathbf{y}, \mathbf{p}^s)}.$$

From equation (2.15), the ratio of the shadow prices can be calculated as:

(2.16)
$$\frac{p_{j,it}{}^s}{p_{h,it}{}^s} = \frac{\partial D_{it}^I(\mathbf{x}, \mathbf{y}) / \partial x_{j,it}}{\partial D_{it}^I(\mathbf{x}, \mathbf{y}) / \partial x_{h,it}}$$

Applying the derivative envelope theory to the numerator and denominator of equation (2.16) results in the following:

$$\frac{p_{j,it}{}^{s}}{p_{h,it}{}^{s}} = \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial x_{j,it}}{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial x_{h,it}} = \frac{\left[1 / \left(D_{it}^{I}(\mathbf{x},\mathbf{y}) \cdot x_{j,it}\right)\right] \cdot \left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{j,it}\right]}{\left[1 / \left(D_{it}^{I}(\mathbf{x},\mathbf{y}) \cdot x_{h,it}\right)\right] \cdot \left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{h,it}\right]} = \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{j,it}}{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{h,it}} \tag{2.17}$$

Finally, substituting equation (2.17) into equation (2.13), the relative allocative inefficiency shown by the relative input price correction indices can then be expressed as:

$$\begin{aligned} k_{jh,it} &= \frac{p_{h,it}}{p_{j,it}} \cdot \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{j,it}}{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y}) / \partial \ln x_{h,it}} \\ &= \frac{p_{h,it}x_{h,it}}{p_{j,it}x_{j,it}} \cdot \frac{\beta_{x_j} + \sum_{h=1}^{N} \beta_{x_{jh}} \ln x_{h,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t}{\beta_{x_j} + \sum_{j=1}^{N} \beta_{x_{jh}} \ln x_{j,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t} \end{aligned} \tag{2.18}$$

2.3 Data

This study will utilize a panel dataset collected from the call report database published online by the Federal Reserve Board of Chicago during period 2000 to 2007. The sample time period allows for the analysis of operating decisions made by the banks around 7 years before the onset of bank failures that started in the end of 2007. Instead of using branch-level data, this study used annualized financial information from consolidated banking financial statements since overall operating decisions, especially concerning input use, are usually made at the banks' head offices. This study's banking database was developed using the following criteria: only banks that continuously reported their financial conditions during the eight-year period were retained and banks with incomplete information for any variable were discarded. These filtering requirements resulted in a total of 9,936 observations (a panel dataset of 1,242 banks over 8 years).

This study classifies banks as either agricultural or non-agricultural banks based on their agricultural loan ratios in 2007 (the start of economic recession) using the Federal Deposit

Insurance Corporation (FDIC)'s classification method where banks are classified as "agricultural" if their farm loans to total loans ratio exceeds 25%. Using this criterion, agricultural banks comprise nearly 30% of the entire sample.

Moreover, this study classifies the bank observations into critically insolvent non-agricultural and surviving/successful agricultural banks. Based on the criterion defined by the FDIC, when a bank's risk-based capital ratio drops below 2%, it is classified by FDIC as "critically undercapitalized". When this happens, FDIC declares the bank as insolvent and will take over management of the bank. In this analysis, the banks considered critically insolvent by the FDIC eventually were declared as bank failures sometime during the period 2007-2012.

The effect of size on efficiencies is also factored into this analysis. A bank's inputs and outputs are normalized by its total assets in each year in order to control the possible impacts from its size.

In this analysis, there are five output data considered: total dollar amounts of agricultural loans (y_1), non-agricultural loans (y_2), consumer loans (y_3), fee-based financial services (y_4), and other assets that cannot be classified under the available asset accounts in the balance sheet (y_5). The input price data categories considered are labor expense per employee (salaries and employee benefits divided by number of full-time equivalent employees, p_1), physical capital (occupancy and fixed asset expenditures divided by net premises and fixed assets, p_2), purchased financial capital inputs (expense of federal funds purchased and securities sold and interest on time deposits of $100,000 or more divided by total dollar value of these funds, p_3), and deposits (interest paid on deposits divided by total dollar value of these deposits, p_4).

Measures of loan quality index (z_1) and financial risk index (z_2) are also included in this analysis to introduce a risk dimension to the efficiency models. The index z_1 is calculated as the ratio of non-performing loans (NPL) to total loans to capture the quality of the banks' loan portfolios (Stiroh and Metli, 2003). The index z_2 is based on the banks' capital to asset ratio, which is used here as proxy for financial risk. The role of equity has been understated in efficiency and risk analyses that focus more on NPL and other liability-related measures (Hughes, Mester, and Moon, 2001). Actually, as a supplemental funding source to liabilities, equity capital can provide cushion to protect banks from loan losses and financial distress. Banks with lower capital to asset ratios (CAR) would be inclined to increasingly rely on debt financing, which, in turn, increases the probability of insolvency. To capture the potential lagged effects from risk factors on bank's efficiency, a three-year moving average transformation was used on both indices.

2.4 Empirical Results

The estimation results for the input distance function (equation 8) for all banks are summarized in table 2.1. The results indicate that the hypothesis that all coefficients of the distance function are equal to zero is rejected at 1% significance level based on the results of an LM test (p-value<0.0001). As discussed earlier, the functional form of the input distance function will affect the consistency of the estimates. The hypothesis that the function takes on the Cobb-Douglas form, which requires that all parameters except for β_{y_k} and β_{j_k} in equation (2) equal to 0, is rejected at 1% significance level by the LM test. This result indicates that the flexible Translog function form is more applicable in this analysis.

The results also indicate that the t statistics for η is insignificantly different from 0 (p-value>0.1). This suggests that the hypothesis of a time-invariant model cannot be rejected and, thus, implies that the TE levels for the sample banks do not change significantly from year to year during the period 2000 to 2007.

2.4.1 Technical Efficiency Estimates

Table 2.2 presents the mean TE level in each bank category. This table also reports the results of the t-tests conducted on the differences in the means of the annual TE levels for all observations in each bank category. The results indicate that agricultural banks that remained solvent and eventually weathered the late 2000s recession operated with significantly higher technical efficiency than those non-agricultural banks that later had solvency problems and eventually failed. The annual TE plots in Figure 2.2 confirm the consistent dominance in efficiency of more successful agricultural banks over their counterparts that became critically insolvent. However, the technical efficiency levels between agricultural banks and non-agricultural banks are not significant under 10% level.

2.4.2 Input Allocation Results

In order to gain a better understanding of the results of the input allocation analyses, a hierarchy of the costs associated with the use of the various inputs need to be established first. Table 2.3 presents a breakdown of the cost shares and the average and marginal costs of the four operating inputs used in this study. Of the four inputs, deposits and labor comprise the larger shares in the banks' total costs (44% and 35%, respectively). The average or unit costs (calculated by dividing specific costs associated with input use and total input units used in the operations) indicate that deposits are the least expensive for all banks, regardless of bank type or financial condition, among the four inputs at $0.016 cost per dollar of deposit. Purchased financial capital and physical capitals' unit costs are $0.024 and $0.172 per dollar of capital used in the operations, respectively. Average labor input cost is $28,749 per employee per year.

The marginal cost (MC) concept can provide a more insightful comparison of input costs as it is related to an input's marginal product (MP).[3] Based on the summary in table 2.3, labor has the most expensive MC at $24,390 while purchased financial inputs have the lowest MC ($0.022). Physical capital's MC is calculated at $.043 while deposits have an MC of $0.040, which is slightly higher than purchased financial inputs' MC.

This cost hierarchy will be the basis for analyzing the estimated input allocation ratios ($k_{jh,it}$). Figure 2.4 plots the k ratios for critically insolvent non-agricultural banks and surviving agricultural banks to easily discern comparative intertemporal patterns of input allocation decisions while table 2.4 shows the input allocation ratio estimates. Between labor and physical capital (k_{12}), both sets of banks overutilized the more costly input (labor) vis-à-vis physical capital inputs. Compared to surviving agricultural banks, critically insolvent non-agricultural banks have managed this sets of inputs more closely to the optimal level (k_{12}=1), and started to underutilize labor in 2007. Between labor and purchased financial inputs (k_{13}), both solvent and insolvent banks have consistently underutilized the more expensive input (labor) and over-utilized financial capital. The results for k_{14} also indicate the same input allocation patterns as both sets of banks have consistently over-utilized labor and underutilized deposits.

As for the other pairs of inputs, both sets of banks, especially the insolvent banks, have over-utilized the more expensive physical capital vis-à-vis deposits (k_{24}) and over-utilized purchased financial inputs, which are cheaper than deposits (k_{34}). Moreover, both sets of banks,

---

[3] Marginal cost is calculated as input price divided by marginal product (MP). MP is calculated as the change in output divided by the change in input level (Pindyck and Rubinfeld, 2009).

have over-utilized purchased financial capital over the more expensive physical capital given the plots of the k_{23} values.

The input allocation ratios for agricultural and non-agricultural banks also reveal similar patterns. In utilizing labor (the most expensive input) relative to other inputs, agricultural banks have persistently favored labor against physical capital and deposits, as shown in k_{12} and k_{14}. Non-agricultural banks also seemed to adopt a similar strategy to overutilize labor, but not as much as agricultural banks, especially when compared to physical capital. Both banks have shown a greater tendency to under-utilize labor relative to purchased financial capital (k_{13}).

Between physical and purchased financial capital inputs (k_{23}), agricultural banks have consistently over-utilized the cheaper input (purchased financial capital), while the non-agricultural banks have allocated these two inputs relatively closer to the prescribed optimal allocation. Both sets of banks have underutilized deposits relative to physical capital inputs (k_{24}) and the purchased financial capital input (k_{34}).

2.4.3 Implications

Among critically insolvent and solvent banks, several implications can be deduced that may have some repercussions in these banks' future financial performance in the latter 2000s.

Both surviving agricultural banks and critically insolvent non-agricultural banks have shown tendencies to adopt more costly labor inputs relative to other cheaper input alternatives, as shown in the results of k_{12} and k_{14}. Compared to non-agricultural banks, agricultural banks have shown greater preference for the over-utilization of labor. This finding is actually consistent with agricultural banks' operational characteristics. On average, agricultural banks selected in this sample have assets of about \$0.12 billion, while non-agricultural banks' assets are estimated at

$0.60 billion. Smaller size and scale has restricted their ability to growth with physical expansion (physical capital). Therefore, agricultural banks (or community banks) heavily rely on their loan officers to interact with loan applicants through building networks, tracking and collecting financial information.

Compared to surviving agricultural banks, critically insolvent non-agricultural banks tend to over-utilize physical capital against deposits. This result suggests that the operating strategy of this group of banks may have been on maximizing investments in physical infrastructure to expand the geographical coverage of their banking operations. Perhaps such expansion entailed the opening of more branches, which may also be supplemented by purchases of more operating equipment and other physical investments. These input allocation decisions are further encouraged by developments in the booming fixed asset markets during the study period where speculative considerations may have guided asset purchase decisions.

On the other hand, successful agricultural banks may have prioritized financial capital build-up during the early 2000s. This group of banks has input allocation ratio results that reveal preference to over-utilize purchased financial capital over other inputs (as shown in k_{13}, k_{23}, k_{34}). Compared to the priorities of insolvent banks that lean more on the more expensive physical capital input, solvent banks have strategically chosen to maximize the utilization of a cheaper input (purchased financial capital), a strategy necessary to minimize these banks' liquidity risk. This is particular true when those agricultural banks are facing higher physical capital costs than their non-agricultural counterparts (as shown in table 2.3).

In the competition for deposit funds, agricultural banks are normally dominated by their larger non-agricultural peers in attracting these funds as the larger non-agricultural banks usually have a more complex package of other financial services that attract more clients (Kliesen and Gilbert, 1996). It is apparent from the input allocation ratios that involve physical capital inputs that non-agricultural banks tend to be more aggressive in the expansion of their physical infrastructure and, perhaps, their geographical clientele coverage (as shown in k_{24}). These input allocation decisions could only, in turn, extend their capabilities to maximize market business opportunities that include, among others, deposit generation.

2.5 Conclusions

This study provides a closer look at the input allocation decisions of several categories of U.S. banks in an earlier time period prior to the late 2000s recession. The technical and allocative efficiency framework was used to discern inefficient input allocation decisions that involve the relative over-utilization and underutilization of certain inputs.

The comparative analysis of input allocation decisions of two groups of banks that eventually either declared bank failures (critically insolvent non-agricultural banks) or survived (surviving agricultural banks) during the late 2000s recession present some interesting implications. In the level of Technical Efficiency, agricultural banks that survived the financial crisis have already dominated the non-agricultural critically insolvent banks before the beginning of recession. However, the level of efficiency for both banks were decreasing when approaching the recession time.

In addition, these banks' input allocation decisions reveal some patterns. Banks that eventually survived the recession have shown greater inclination to prefer cheaper inputs while the critically insolvent banks of the late 2000s utilized more expensive inputs. For instance, compared to the survival banks, the banks that eventually failed underutilized financial capital and deposits relative to physical capital during that period. These banks seemed to have adopted physical capital buildup strategies over other priorities. In the early 2000s, the federal funds effective rate decreased from 6.24% in 2000 to 1.35% in 2004 with deposit rates following almost the same rate of decline (Board of Governors, 2007).

The contrasting input utilization decisions of the two groups of banks are consistent with the predictions of a previous study (Li et al., 2013). Specifically, such study contends that decisions on funding arrangements, interest rate risk and asset portfolio composition that favor more costly alternatives can be possible predictors of eventual bank failures several years after these decisions were made. This study's results clearly establish that operating decisions in input allocations based on established priorities can have important implications on the banks' eventual performance and survival through economic adversities. In this study, the prioritization of liquidity risk management strategies has enhanced the relative financial strength of banks over those that leaned more on physical asset expansion.

As agricultural banking operations are usually smaller in size and scale than non-agricultural banks, it seems that such traits are not necessarily limiting and adversarial. Instead, agricultural banks are pressured to make more regulated, if not perfectly efficient or optimal, decisions on the utilization of certain inputs, like over-utilizing labor and underutilizing physical capital, with their size limitation under consideration. Agricultural banks seemed to have concentrated more on financial capital build-up while their non-agricultural banking peers have focused more on physical capital expansion. Indeed, certain limitations can at times present opportunities for better prudent and beneficial decisions. It is therefore not surprising that agricultural banks have fared considerably well through such difficult economic downturn of the late 2000s.

Table 2.1. Estimation Results for the Input Distance Function

Model Coefficients and Parameter Estimates									
Intercept	2.473 (1.525)	$\beta_{x_{44}}$	0.119*** (0.013)	$\beta_{xy_{11}}$	-0.009*** (0.002)	$\beta_{yz_{11}}$	0.001** (0.001)	α_3	0.002*** (0.0003)
β_{y_1}	-0.092*** (0.016)	$\beta_{z_{11}}$	-0.005*** (0.001)	$\beta_{xy_{12}}$	-0.024** (0.011)	$\beta_{yz_{21}}$	0.002 (0.003)	α_4	-0.0002 (0.001)
β_{y_2}	-0.317*** (0.078)	$\beta_{z_{22}}$	0.082*** (0.018)	$\beta_{xy_{13}}$	-0.011** (0.004)	$\beta_{yz_{31}}$	0.0001 (0.001)	α_5	0.002*** (0.0005)
β_{y_3}	-0.032 (0.029)	$\beta_{y_{12}}$	0.010*** (0.002)	$\beta_{xy_{14}}$	-0.0001 (0.004)	$\beta_{yz_{41}}$	0.001 (0.001)	δ_1	-0.002** (0.001)
β_{y_4}	0.058* (0.031)	$\beta_{y_{13}}$	0.002* (0.001)	$\beta_{xy_{15}}$	0.028*** (0.006)	$\beta_{yz_{51}}$	0.0004 (0.002)	δ_2	0.001** (0.0003)
β_{y_5}	0.145** (0.046)	$\beta_{y_{14}}$	0.003** (0.001)	$\beta_{xy_{21}}$	-0.002* (0.001)	$\beta_{yz_{12}}$	0.002 (0.002)	δ_3	0.0001 (0.0005)
β_{x_1}	0.058 (0.049)	$\beta_{y_{15}}$	-0.005*** (0.001)	$\beta_{xy_{22}}$	-0.004 (0.004)	$\beta_{yz_{22}}$	-0.016** (0.011)	δ_4	0.001 (0.001)
β_{x_2}	0.087** (0.034)	$\beta_{y_{23}}$	0.012** (0.004)	$\beta_{xy_{23}}$	-0.004** (0.002)	$\beta_{yz_{32}}$	0.008* (0.005)	θ_1	-0.001** (0.0003)
β_{x_3}	0.367*** (0.036)	$\beta_{y_{24}}$	0.003 (0.005)	$\beta_{xy_{24}}$	-0.001 (0.002)	$\beta_{yz_{42}}$	0.009* (0.005)	θ_2	-0.002* (0.001)
β_{x_4}	0.489*** (0.070)	$\beta_{y_{25}}$	-0.031*** (0.006)	$\beta_{xy_{25}}$	0.001 (0.003)	$\beta_{yz_{52}}$	0.004 (0.007)	λ_1	-0.0002 (0.007)
β_{z_1}	0.013 (0.022)	$\beta_{y_{34}}$	0.013*** (0.002)	$\beta_{xy_{31}}$	-0.007*** (0.001)	$\beta_{xz_{11}}$	0.002 (0.003)	λ_2	-0.002 (0.0001)
β_{z_2}	-0.234*** (0.092)	$\beta_{y_{35}}$	-0.009*** (0.002)	$\beta_{xy_{32}}$	-0.044*** (0.005)	$\beta_{xz_{21}}$	0.0002 (0.001)	d_a	-0.005 (0.006)
$\beta_{y_{11}}$	-0.001** (0.001)	$\beta_{y_{45}}$	-0.010** (0.003)	$\beta_{xy_{33}}$	-0.003 (0.002)	$\beta_{xz_{31}}$	-0.005*** (0.002)	η	-0.001 (0.002)
$\beta_{y_{22}}$	0.015 (0.012)	$\beta_{x_{12}}$	0.015** (0.005)	$\beta_{xy_{34}}$	0.010*** (0.003)	$\beta_{xz_{41}}$	0.002 (0.003)		
$\beta_{y_{33}}$	0.012*** (0.002)	$\beta_{x_{13}}$	0.033*** (0.005)	$\beta_{xy_{35}}$	-0.002 (0.003)	$\beta_{xz_{12}}$	-0.063*** (0.012)		
$\beta_{y_{44}}$	0.009*** (0.003)	$\beta_{x_{14}}$	-0.026** (0.008)	$\beta_{xy_{41}}$	0.018*** (0.002)	$\beta_{xz_{22}}$	0.024** (0.005)		
$\beta_{y_{55}}$	0.006 (0.005)	$\beta_{x_{23}}$	-0.010*** (0.002)	$\beta_{xy_{42}}$	0.071*** (0.012)	$\beta_{xz_{32}}$	-0.002 (0.001)		
$\beta_{x_{11}}$	-0.022*** (0.006)	$\beta_{x_{24}}$	-0.007 (0.005)	$\beta_{xy_{43}}$	0.018*** (0.005)	$\beta_{xz_{42}}$	0.041 (0.014)		
$\beta_{x_{22}}$	0.002 (0.003)	$\beta_{x_{34}}$	-0.086*** (0.006)	$\beta_{xy_{44}}$	-0.009* (0.005)	α_1	-0.003* (0.0002)		
$\beta_{x_{33}}$	0.063*** (0.004)	$\beta_{z_{12}}$	0.009** (0.003)	$\beta_{xy_{45}}$	-0.027*** (0.007)	α_2	0.0002 (0.001)		

Notes: *** Significantly different from zero at the 1% confidence level.
** Significantly different from zero at the 5% confidence level.
* Significantly different from zero at the 10% confidence level.

Table 2.2. Technical Efficiency Levels and Mean Differences, Banks Categorized By Solvency and Specialization

Category	Estimate	Standard Error	t Value	Pr> |t|
By Specialization				
Agricultural Banks	0.3424	0.0003		
Non-Agricultural Banks	0.3429	0.0004		
Difference between Means	0.0005	0.0006	0.8424	0.3996
By Solvency				
Agricultural Survival Banks	0.3423	0.0004		
Non-Agricultural Critically Insolvent Banks	0.3399	0.0012		
Difference between Means	0.0024	0.0012	2.0157	0.0439

Table 2.3. Comparative Cost Profiles of Operating Inputs, All Banks, 2000-2007

Inputs	Average Costs ($ per unit of input)	Marginal Costs ($ per Marginal Product)	Share in Total Costs
All Banks			
Labor	28,749	24.390	35%
Physical Capital	0.172	0.043	9%
Purchased Financial Inputs	0.024	0.022	12%
Deposits	0.016	0.040	44%
Critically Insolvent Non-Agricultural Banks			
Labor	30,710	76.937	34%
Physical Capital	0.144	0.054	9%
Purchased Financial Inputs	0.024	0.072	15%
Deposits	0.017	0.138	42%
Surviving Agricultural Banks			
Labor	29,088	17.259	34%
Physical Capital	0.207	0.047	8%
Purchased Financial Inputs	0.024	0.019	11%
Deposits	0.017	0.038	47%
Agricultural Banks			
Labor	29,049	17.127	34%
Physical Capital	0.207	0.047	8%
Purchased Financial Inputs	0.024	0.019	11%
Deposits	0.017	0.038	47%
Non-Agricultural Banks			
Labor	28,624	27.400	35%
Physical Capital	0.157	0.041	9%
Purchased Financial Inputs	0.023	0.023	13%
Deposits	0.016	0.041	43%

Table 2.4. Input Allocation Ratios ($\boldsymbol{k_{jh}}$) by Bank Categories, Annual Averages, 2000-2007

Bank Categories	Year	k12[a]	k13[b]	k14[c]	k23	k24	k34
A. By Solvency							
	2000	0.71	2.24	0.20	6.09	0.43	0.14
	2001	0.89	2.54	0.21	4.59	0.35	0.12
	2002	0.84	1.26	0.16	2.13	0.24	0.14
Critically Insolvent Banks	2003	0.83	1.26	0.14	2.33	0.20	0.14
	2004	0.81	1.22	0.12	2.30	0.17	0.13
	2005	0.85	1.19	0.14	2.03	0.21	0.13
	2006	0.99	1.60	0.19	2.82	0.27	0.14
	2007	1.15	1.48	0.22	2.00	0.27	0.17
	2000	0.42	2.15	0.19	6.40	0.59	0.15
	2001	0.45	2.22	0.20	6.21	0.57	0.14
	2002	0.41	1.67	0.14	5.46	0.43	0.44
Successful (Solvent) Banks	2003	0.40	1.42	0.10	4.87	0.34	0.12
	2004	0.39	1.23	0.08	4.12	0.27	0.13
	2005	0.40	1.41	0.10	4.77	0.32	0.13
	2006	0.43	1.88	0.13	6.24	0.41	0.11
	2007	0.45	2.07	0.16	6.53	0.47	0.11
***B.* By Specialization**							
	2000	0.42	2.16	0.19	6.38	0.59	0.15
	2001	0.46	2.21	0.20	6.17	0.57	0.14
Agricultural Banks	2002	0.41	1.67	0.14	5.43	0.43	0.14
	2003	0.40	1.42	0.10	4.87	0.34	0.12
	2004	0.39	1.23	0.08	4.12	0.27	0.13
	2005	0.40	1.40	0.10	4.74	0.32	0.12
	2006	0.43	1.87	0.13	6.21	0.41	0.11
	2007	0.45	2.07	0.16	6.49	0.47	0.12
	2000	0.58	2.42	0.19	6.25	0.47	0.13
	2001	0.71	2.35	0.20	5.20	0.41	0.13
Non Agricultural Banks	2002	0.67	1.68	0.14	4.01	0.31	0.13
	2003	0.64	1.33	0.11	3.32	0.24	0.13
	2004	0.67	1.15	0.09	2.94	0.20	0.12
	2005	0.70	1.38	0.11	3.20	0.23	0.12
	2006	0.75	1.76	0.15	4.29	0.31	0.12
	2007	0.74	2.00	0.17	4.80	0.34	0.12

Notes: [a] Input 1 is labor while input 2 is physical capital
[b] Input 3 is purchased financial capital
[c] Input 4 is deposits.

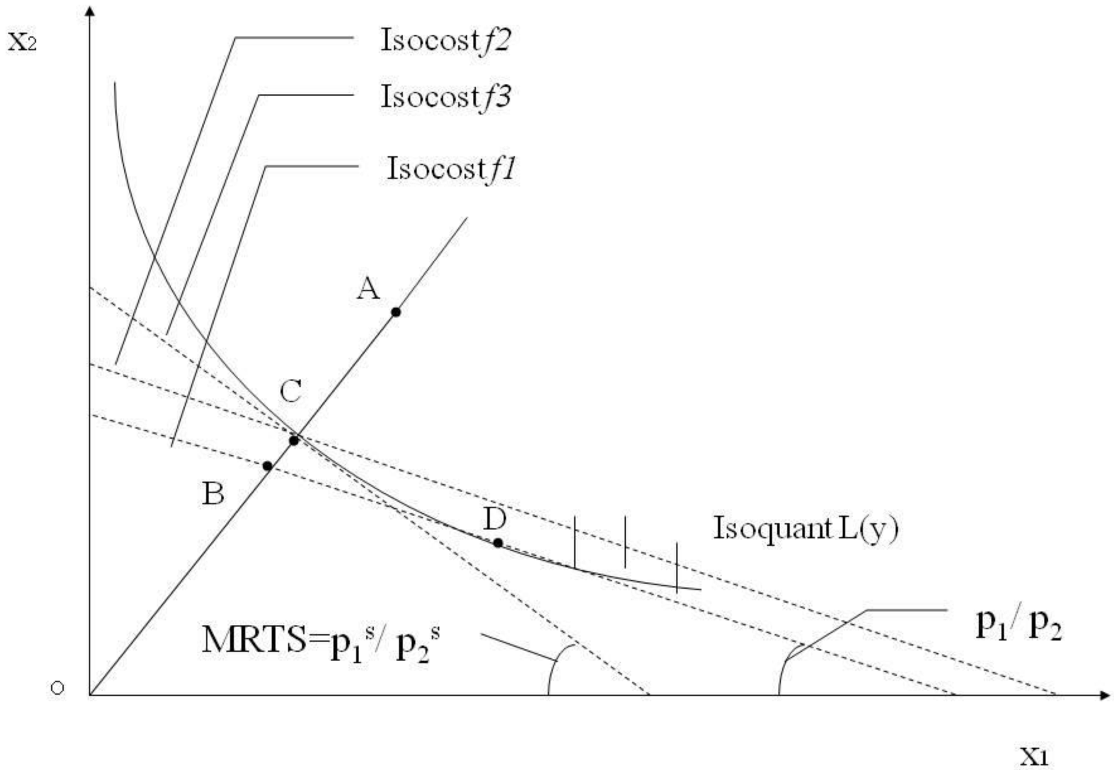

Figure 2.1. Technical and Allocative Efficiency Identified by Input Distance Function

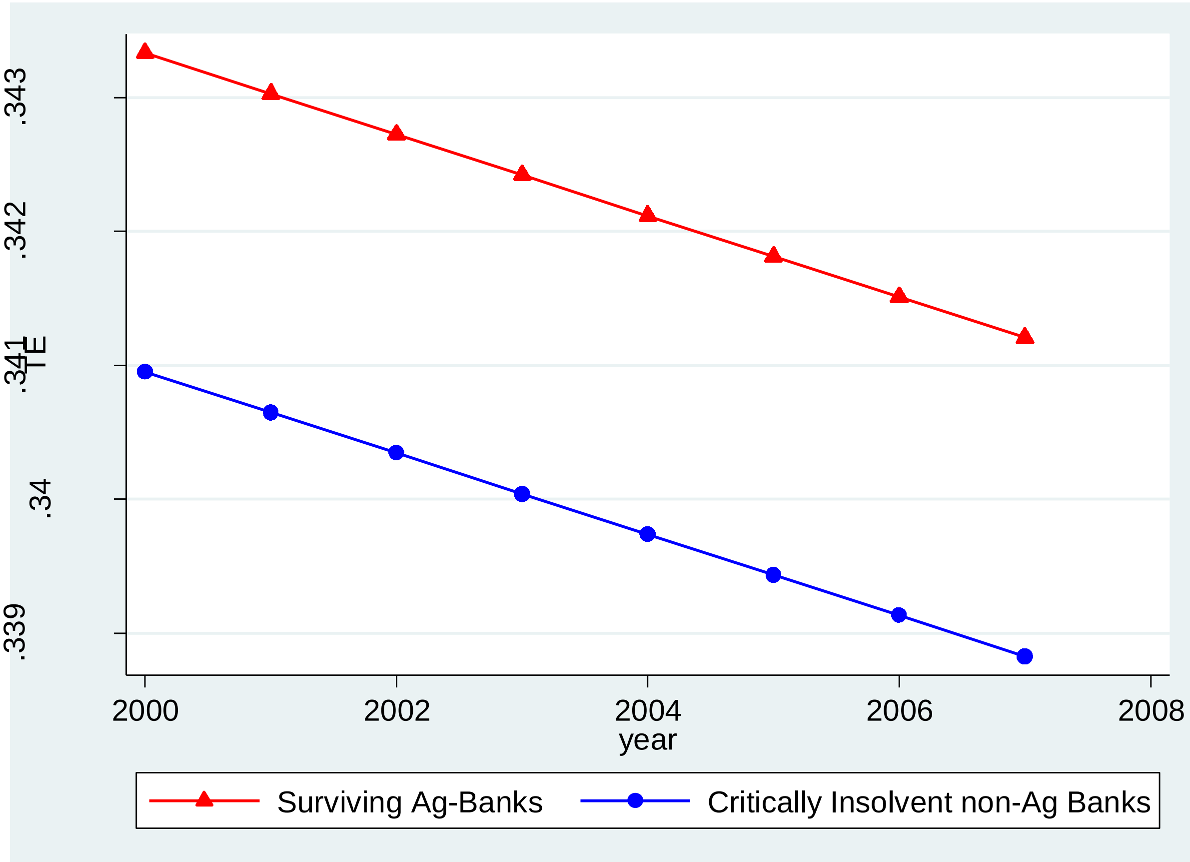

Figure 2.2. Trends in Technical Efficiency Levels, By Bank Solvency Category, 2000-2007

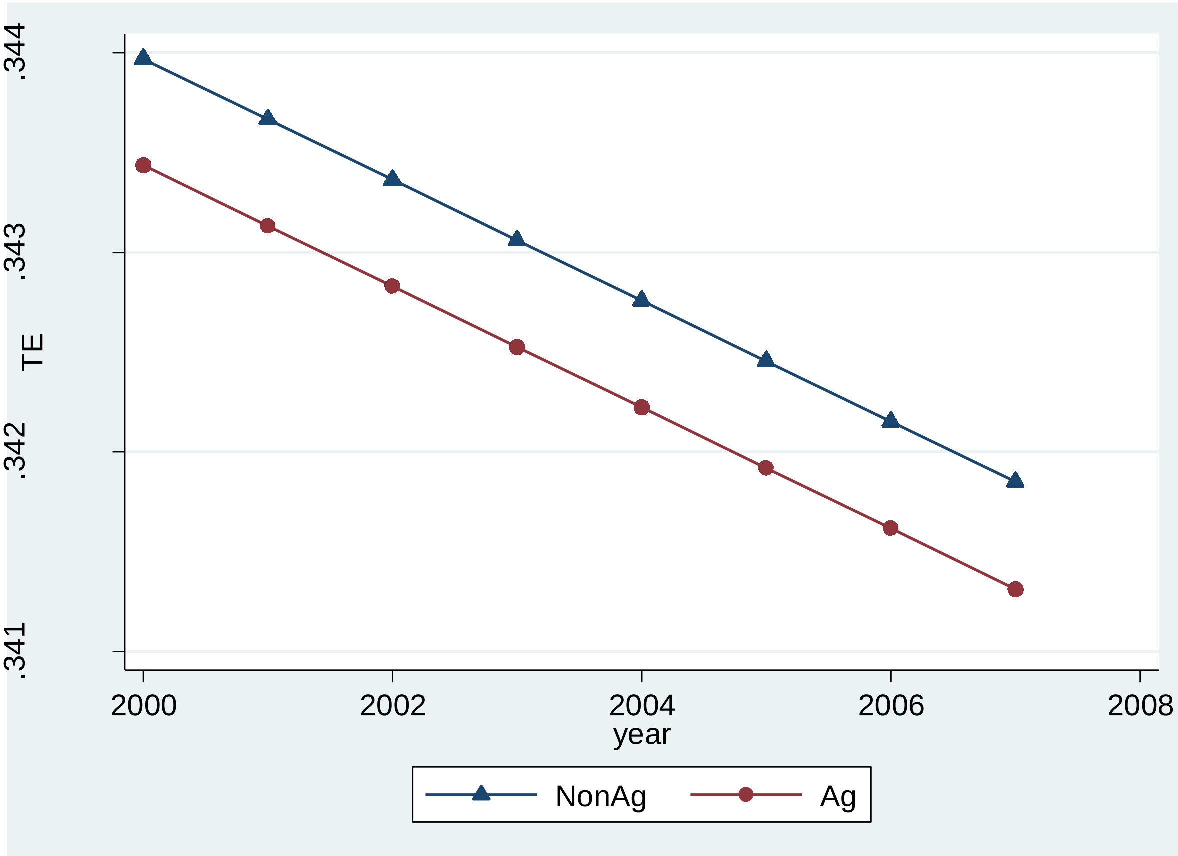

Figure 2.3: Trends in Technical Efficiency Levels, By Bank Specialization Category, 2000-2007

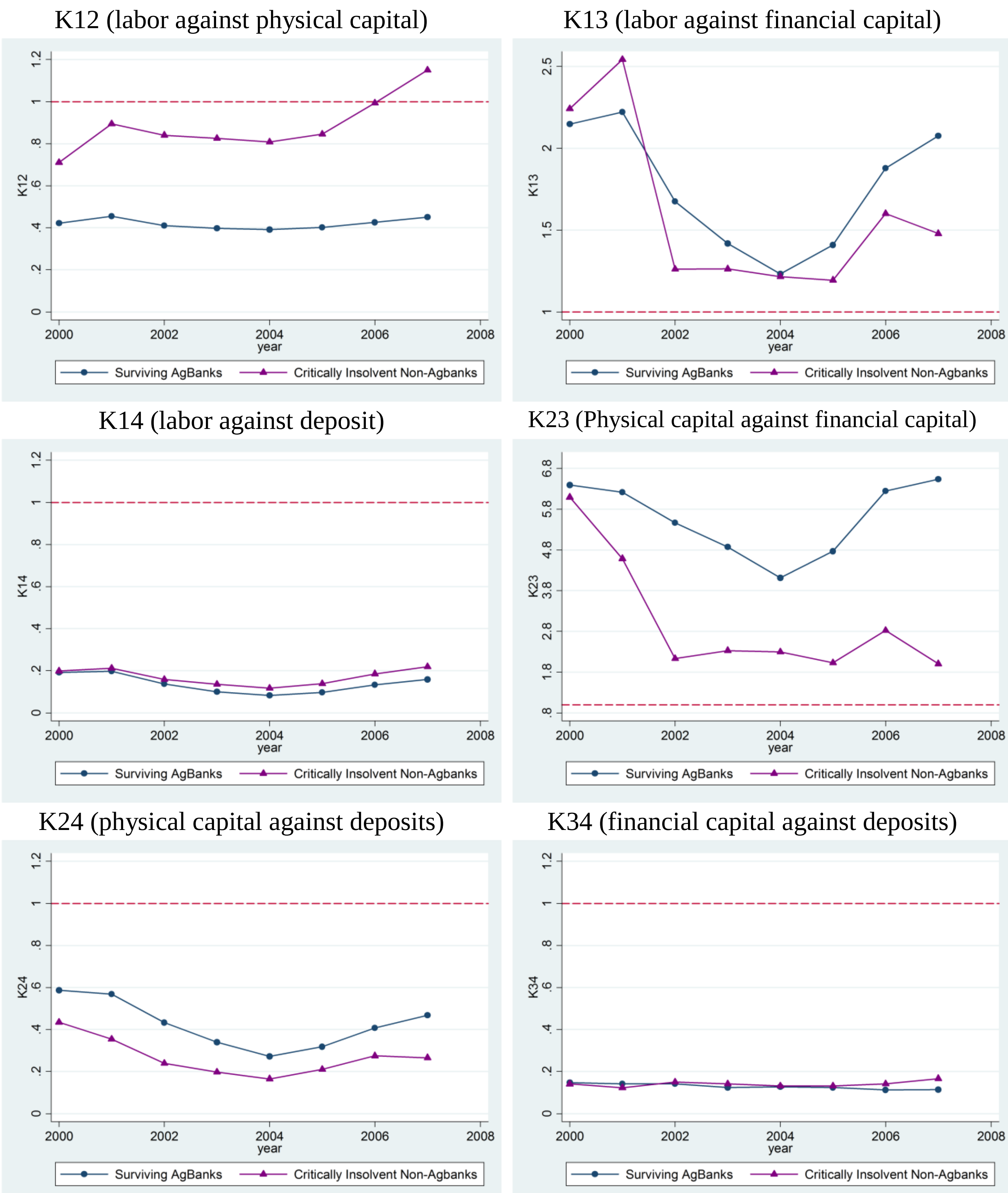

Figure 2.4: Plots of Input Allocation Ratios (k_{jh}) by Bank Solvency Category, 2000-2007

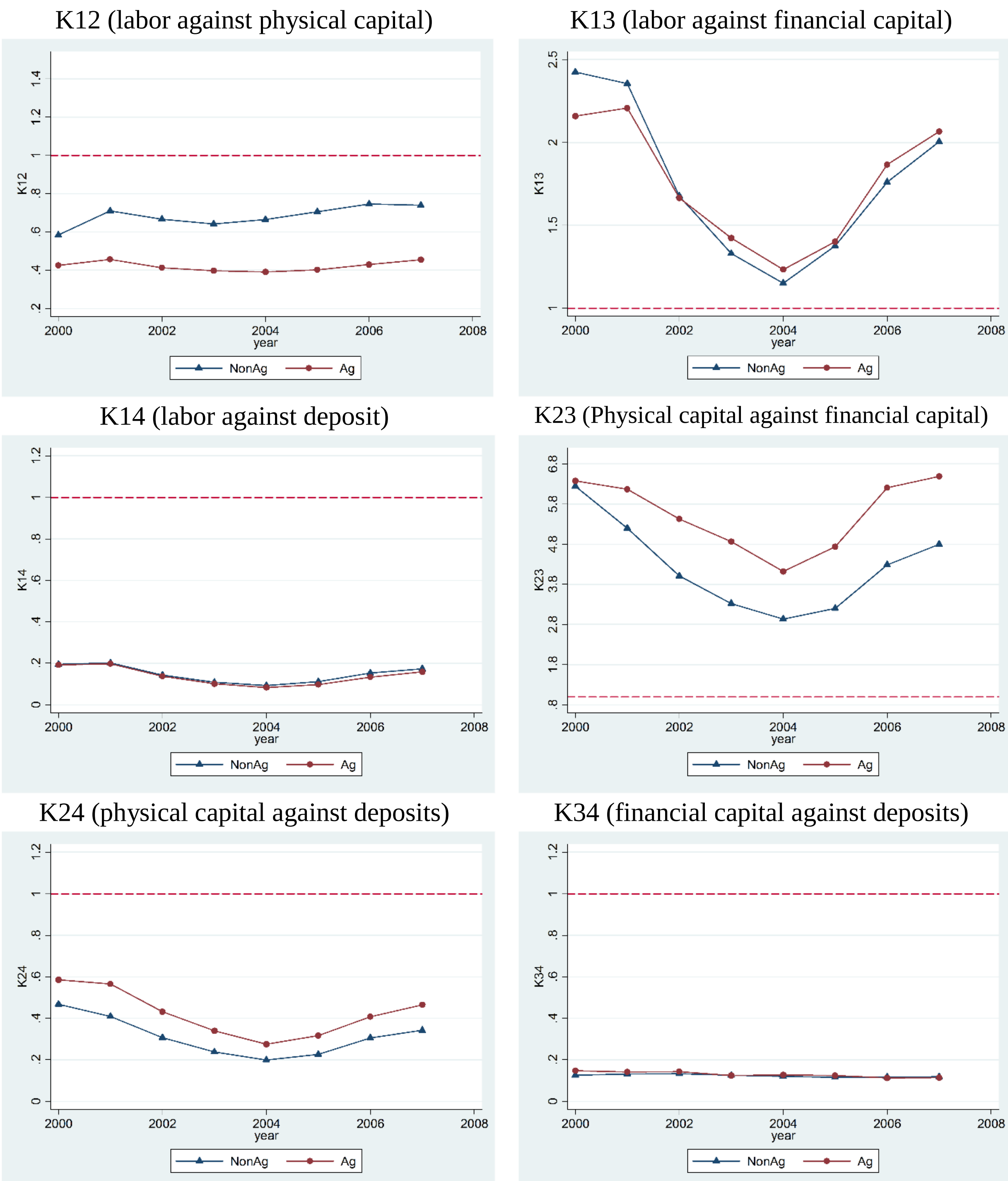

Figure 2.5: Plots of Input Allocation Ratios (k_{jh}), by Bank Specialization Category, 2000-2007

CHAPTER 3

A Split-Population Duration Approach to Understanding Agricultural Banking Survival Strategies during the Late 2000s Recession

3.1 Introduction

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 operating conditions of farm businesses usually subject the farms to unique sources of risk and uncertainty often not faced by other industries (e.g. weather, pests, diseases and other factors affecting productivity, marketing and other areas of operations).

Such perceptions of the potential business vulnerability of farm businesses are often translated to high credit risks. As banking failures plagued the financial industry during the late 2000s recession, some experts suspected that significant loan exposures to agricultural activities could increase the probability of bank failure (Rozycki, 2009; Vogt, 2009; Henderson and Akers, 2010). Such paranoia has some historical basis. Still fresh in the mind among many people is the memory of the 1980s farm crisis, 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 (Peoples et.al, 1992; Belongia and Gilbert, 1987).

The National Bureau of Economic Research (NBER) contends that the late 2000s economic recession caused some serious economic repercussions for the local and global economies (NBER, 2010). This most recent recession, characterized by high unemployment, declining real estate values, bankruptcies and foreclosures, affected the banking industry so severely that nearly 500 banks failed from 2007 until the end of 2014. During this time, the number of critically insolvent banks included in the "High Risk of Failing Watch List" maintained by Federal Deposit Insurance Corporation (FDIC) also increased dramatically.

Daniel Rozycki, associate economist of Federal Reserve Bank of Minneapolis, actually pointed out some similarities of the late 2000s recession to the 1980s farm crisis in recent agricultural sector trends (Rozycki, 2009). He observed that the prices of some key crops doubled or tripled from 2006 to 2008 but started on a downhill trend thereafter (except in 2012 and 2013) while farmland prices were falling after reaching record high levels in 2008. There has been some concern that a continued decline in land and crop prices could lead to deterioration in the agricultural loan portfolios of commercial banks and other farm lenders.

It has been argued that no financial crisis can be dismissed as insignificant since any crisis that affects all or even just a part of the banking sector may result in a decline in shareholders' equity value, the loss of depositors' savings, and insufficient funding for borrowers. These would translate to increasing costs on the economy as a whole (Hoggarth et al. 2002). In this regard, it is important to probe more deeply and understand the causes of the bank failures experienced in the banking industry during the last recession as this could provide insights on more effective, cautious operating decisions that could help prevent the duplication of failures in the future.

Most early warning banking studies that have already been published have employed probit/logit techniques in their analyses (Hanweck, 1977; Martin, 1977; Pantalone and Platt, 1987; Thomson, 1991; Cole and Gunther, 1998). The analyses are usually focused on identifying retroactive determinants of a bank's probability of failure versus survival.

Duration (hazard) models were introduced as an alternative to the probit/logit technique in identifying the determinants of the probability of bank failure. The original application of this model was introduced by Cox in a biomedical framework (Cox, 1972). In banking, the Cox proportional hazard model was first applied in 1986 to explain bank failure (Lane et al., 1986). The cox model adopts a semi-parametric function that offers the advantage of avoiding some of the strong distributional assumptions associated with parametric survival-time models. However, just as in other parametric duration models, the Cox proportional model suffers from one shortcoming whereby it forces the strong assumption of the eventual failure of every single observation analyzed by the model. Hence, the model is incapable of isolating specific determinants of bank failure from factors that influence the timing of failure.

The split-population duration model was conceived as a remedy to such shortcoming. The model was first used by Schmidt and Witte (1989) in a study on making predictions on criminal recidivism. The study recognizes the irrationality in assuming that every individual would eventually return to prison. As such, the study's sample has been "split" into those that "(did go) back to prison" and "(did) not (go) back to prison". The model was actually applied to the analyses of bank failures in previous economic episodes other than the more recent banking crises caused by the last recession (Cole and Gunter, 1995; Hunter et al., 1996; Deyoung, 2003).

This paper presents an application of the split-population duration model to the banking crisis in the late 2000s recession. Specifically, this article will identify early bank failure warning signals that can be deduced from the operating decisions made and lessons learned by banks that either failed or survived the last recession. This study differentiates itself from previous empirical works through its focus on factors that affect both the comparative financial (probability of survival) and temporal (length of survival) endurance of commercial banks. In this analysis, special attention will be given to the role of agricultural loan portfolios in influencing a bank's length and probability of survival, given the previous track record of farm credit transactions in affecting lenders' financial health during the 1980s financial crises. The strength and reliability of this study's results lie in its underlying analytical framework's capability to capture more realistic and intuitively reasonable assumptions on the probability and timing of failure that should rectify results in other studies that do not account for such conditions.

3.2 The Analytical Framework

This study's analytical framework is derived from basic survival analysis techniques used in previous empirical studies (Schmidt and Witte, 1989; Cole and Gunther, 1995; Deyoung, 2003). The likelihood function for the basic parametric survival model can be written as:

$$(3.1) \qquad L = \prod_{i=1}^{N} [\mathrm{f}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{1-\mathrm{D_i}} [\mathrm{S}(\mathrm{t_i} \mid \mathrm{p}, \lambda)]^{\mathrm{D_i}}$$

where $f(\mathrm{t})$ is the probability density function of duration t and $S(\mathrm{t})$ is the survival function. D_i is the indicator variable that would equal to one if a bank survived the entire sample period and would equal to zero if the bank was shut down during the period. As pointed out in previous split-population duration studies (Schmidt and Witte, 1989, Cole and Gunther, 1995, Deyoung, 2003), the basic duration model's shortcoming lies in its forced assumption that every observation in the dataset will eventually experience the event of interest; or as applied to this analysis, the assumption that every bank would eventually fail as time at risk becomes sufficiently large. The other shortcoming, as pointed out by Cole and Gunther (1995), is that the likelihood function fails to distinguish between the determinants of failure and those influencing the timing of failure. These issues are addressed in the subsequent discussions.

Using the notation from Schmidt and Witte (1989), F is defined to be an unobservable variable that equals to 1 if the bank eventually fails and 0 otherwise. Then,

(3.2) $$P(\mathrm{F}=1)=\delta, \quad P(\mathrm{F}=0)=1-\delta$$

where the estimable parameter δ is the probability that a bank will eventually fail. With this additional parameter, the basic likelihood function to be estimated is modified as follows:

(3.3) $$L=\prod_{i=1}^{N} [\delta\,\mathrm{f}(\mathrm{t_i}\mid \mathrm{p},\lambda)]^{1-\mathrm{D_i}}[(1-\delta)+\delta\,\mathrm{S}(\mathrm{t_i}\mid \mathrm{p},\lambda)]^{\mathrm{D_i}}$$

If $\delta=1$, then the likelihood function reduces into a "basic" duration model that assumes all banks will eventually fail. If $\delta<1$, then both $S(\mathrm{t})$ and $f(\mathrm{t})$ are estimated conditional on the probability of bank failure.

In bank failure studies, the log-logistic distribution has been widely used (Cole and Gunther, 1995, Deyoung, 2003) since it is a non-monotonic hazard function that can generate a hazard rate that increases initially before eventually decreasing. The log-logistic distribution imposes the following form on the survival function $S(\mathrm{t})$ and hazard function $h(\mathrm{t})$:

(3.4) $$S(\mathrm{t})=\frac{1}{1+(\lambda\,\mathrm{t})^{\mathrm{p}}}$$

(3.5) $$h(\mathrm{t})=\frac{f(\mathrm{t})}{S(\mathrm{t})}=\frac{\lambda p(\lambda\,\mathrm{t})^{\mathrm{p}-1}}{1+(\lambda\,\mathrm{t})^{\mathrm{p}}}$$

Given the above, the shape of probability density function can be obtained from the product of equations (3.4) and (3.5) as shown below:

(3.6) $$f(\mathrm{t})=\mathrm{S(t)\,h(t)}=\frac{\lambda p(\lambda\,\mathrm{t})^{\mathrm{p}-1}}{[1+(\lambda\,\mathrm{t})^{p}]^{2}}$$

where parameters p and λ are positive parameters that define the exact shape of this hazard function.

The probability of eventual bank failure δ and the timing of failure λ can be made bank-specific as follows:

$$\delta = \frac{1}{1+e^{\alpha' X}}$$

(3.7)

$$\lambda = e^{-\beta' X}$$

where X is a vector of covariates that capture the influence of a bank's financial condition on δ and λ.

The parameters α and β are estimated in the split-population duration model, with α representing a direct relationship between bank specific covariates and the probability of survival, and β indicating a direct relationship between those covariates and survival time.

The variables used in this study and their descriptive statistics are shown in table 3.1. In order to distinguish each variable' effect on both the probability of survival and length of survival, identical regressors are used in the estimation of α and β parameters. This approach has been employed in several empirical studies (Douglas and Hariharan, 1994; Cole and Gunther, 1995; DeYoung, 2003) and this study is an attempt to duplicate such analytical method. The following sub-sections discuss the measurement of the explanatory variables considered in this analysis and their expected relationships with the dependent variables (table 3.1).

3.2.1 Asset Quality and Management Risk Variables

Bank loan concentration is measured in this model by HHI, calculated as the Herfindahl-Hirschman Index, which is bounded as follows:

$$\frac{1}{n} \leq HHI \leq 1$$

where n stands for the loan segments. This index will approach 1 under higher levels of client specialization (or if banks tend to concentrate their loan portfolios around one or just a few client categories). An index that approaches 0 indicates a more diversified loan portfolio. This variable is designed to measure portfolio diversification that is usually regarded as a risk reduction strategy (Markowitz, 1952; Thomson 1991; DeYoung and Hasan, 1998). This index is expected to be negatively related to both the probability of bank's survival and expected survival time[4].

Management risk will be captured in the model by two measures: overhead cost ratios (OVERHEAD) and insider loan ratios (INSIDER) (Whalen,1991; Thomson, 1991). OVERHEAD is calculated as the sum of salaries and employee benefits, expense on premises and fixed assets, and total noninterest expense divided by average total assets. This ratio is expected to negatively influence the likelihood of survival since improved management of these expenses would increase bank's efficiency and therefore increase its survival probability. The insider loan ratios (INSIDER) is calculated by dividing the aggregate amount of credit extended to the banks' officers, directors

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[4] The index was developed using Herfindahl measurement method where the index was constructed from taking the sum of squares of various components of the loan portfolio:

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

and stockholders to total assets. Thomson (1991) used this ratio to capture management risk in the form of fraud or insider abuse, and it is expected to be negatively related to both the probability of survival and expected survival time.

3.2.2 Profitability Potential and Structural Variables

PROFIT, represented by the rate of return on assets, captures the banks' earnings capability and it is expected to increase both the probability of survival and expected survival time. To capture the effect of the size and scale of banking operations, the logarithm of total assets (SIZE) is included in this model (Cole and Gunther, 1995; Wheelock and Wilson, 2000; Shaffer, 2012). Compared to smaller banks that possibly do not have adequate resource capability to withstand economic crises, larger banks are more likely expected to survive since they possess greater financial flexibility and larger resource bases to weather economic fluctuations.

3.2.3 Loan Portfolio Composition and Non-Performing Loan Variables

The banks' loan exposures to different industry sectors are also accounted for in the model, as suggested by previous literatures (Cole and Gunter, 1995; Wheelock and Wilson, 2000; DeYoung, 2003). These variables include the proportion to total loans of loan exposures to specific industry segments such as agriculture (AGLOANS), consumer (CONSUMLOANS), and commercial & industrial (CILOANS) sectors[5]. These variables' impact on survival probability and time may vary depending on the relative financial health of each sector.

The banks' credit risk conditions are captured by several variables that capture the actual delinquency rates experienced in certain loan categories. These categories or transaction categories

[5] Real Estate Loans to Total Loan ratio is removed due to multicollinearity issue in this sample.

include agricultural (AGNP), real estate (REALESTNP), commercial and industrial (CINP), and consumer (CONSUMNP) loan transactions. The aggregate value of actual non-performing loans in each transaction category is calculated as the sum of "past due up to 89 days", "past due 90 plus days", and "nonaccrual or charge-offs". The measures for these variables are calculated as the proportion of delinquencies in each transaction category to the aggregate value of the loan portfolio in each category, and weighted by their corresponding loan categories to total loan ratio.

3.2.4 Funding Arrangement Variables (FA)

Banks may hold portfolios of assets and liabilities with different maturities and a change in interest rates will affect the portfolios' market value and net income. Interest rate risk is represented by three variables. The first variable is measured as the proportion of Purchased Liabilities to Total Liabilities (PURFUNDS). As a price-taker in the national market, banks that rely more on external markets through higher purchases of liabilities will incur greater interest expenses and, hence, may have lower probabilities of survival (Belongia and Gilbert, 1990).

The other measure is GAP and is derived by first subtracting "liabilities with maturities less than one year" from "assets with maturities less than one year" and then dividing the difference by total assets (Belongia and Gilbert, 1990). This GAP ratio is expected to be negatively related to both the probability of survival and survival time since banks can lose their market value when interest rates rise.

The third variable, DEPLIAB, is calculated by taking the ratio of total deposits to total liabilities. This ratio is expected to be positively related to the likelihood of survival and bank's survival time because bank's tendency to thrive in the business is enhanced by their ability to attract deposits to provide loans.

3.3 Data Description

The banking data used in this study are collected from the quarterly Consolidated Reports of Condition and Income (call reports) published online by the Federal Reserve Bank of Chicago (FRB). A dataset of banks that either failed or survived after December 2007 through the fourth quarter of 2012 was developed for this study. This time period adequately captures the late 2000s recession, which was said to have formally started in December 2007 (NBER, 2008). The reckoning (starting) point for each bank's survival period is set at the end of the 4th quarter of 2007. Some previous studies have considered using time-varying covariates in their duration models applied to panel datasets (Wheelock and Wilson, 2000; Dixon et al, 2011). However, Chung (1991) contends that the unique design of the split-population duration model does not allow the explanatory variables to vary over time while it is relatively straightforward and feasible to incorporate the time-varying design in a proportional hazard model. Hence, this analysis employs the more applicable cross-sectional data analysis for its split-population model.

The maximum survival time is censored at 21 quarters. Banks that commenced operations after December 2007 were not included in the dataset to ensure the right censoring of data. The right censoring design used in this analysis follows the approach used in earlier studies that does not account for the interval censoring of failed banks, which assumes that banks may fail in a give time period (Cole and Gunter, 1995; Deyoung, 2003; Maggiolini and Mistrulli, 2005)[6]. Surviving or successful banks during the time period that have missing values for any financial data being collected were discarded. Given these data restrictions, the resulting sample of 6,839 banks

[6] An interval censoring design approach is beyond the scope and capability of this paper, as has also been the case of similar studies this article is drawn from. Future research efforts may be devoted to validating the use of such design.

consists of 6,461 surviving and 378 failed bank observations. These banks' financial performance indicators measured by the end of 2007 were used for this analysis.

3.4 Estimation Results

Prior to estimation, an important preliminary step is to check the appropriateness of the distributional assumption by comparing the split-population's hazard rate[7] and the actual hazard rate (Douglas and Hariharan, 1994; Cole and Gunter, 1995). This is achieved by estimating a split-population model without covariates and comparing the predicted hazard to a nonparametric estimate. The nonparametric hazard estimate is calculated by dividing the number of failed banks at time t by the number of banks that neither failed nor were censored in prior periods.

As shown in figure 3.1, the nonparametric hazard rate rises rapidly from quarter 2 to quarter 8 (2009 third quarter) and would decrease at a slower pace from quarter 11 to quarter 21 ($S(\mathrm{T}) = 1$ at quarter 1). This trend in the changes in the hazard rate is closely replicated by the behavior of the forecasts by the split-population model using the log-logistic distribution as the underlying parametric distribution.

Table 3.2 presents the estimation results for both the determinants of the probability of survival and each bank's survival time under the split population duration model.

3.4.1 Determinants of the Probability of Survival

As laid out in this study's analytical model, the covariates associated with α measure their impact on the probability of a bank's survival. A positive coefficient result indicates a higher probability of survival.

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[7] The hazard rate is calculated from an unconditional hazard function $h(\mathrm{t}) = \delta(\mathrm{t}) / [(1-\delta) + \delta S(\mathrm{t})]$.

This study’s results focused on certain loan portfolio composition variables that identify specific sectors that can be accommodated by banks in order to enhance their chances of survival. Results indicate that the banks’ consumer loan exposure (CONSUMLOANS) has a significant, favorable effect on their probability of survival, which is consistent with the findings from Cole and Whitt (2012) who claimed that banks have comparative advantage in well-behaved consumer loans. The estimated coefficients for agricultural (AGLOANS) and industrial (CILOANS) loans, on the other hand, are not significant.

Among the non-performing loan variables that capture client delinquency in several loan categories, this study’s most compelling result is the insignificance of the agricultural loans-related variable (AGNP). These results suggest that the delinquency ratio of those loans extended to agricultural businesses cannot be used as an effective indicator for predicting bank failures. It has been observed that the agricultural economy, supported by strong global demand for agricultural products and an expanding biofuel sector, was booming. This finding is also confirmed by some empirical studies on the latest recession (Li et al., 2013; Sundell and Shane, 2012) that provide further support on the financial strength of the agricultural sector.

In contrast, delinquency loan ratio variables for real estate loans (REALESTNP), and consumer loans (CONSUMNP) are significant negative regressors. The significant effect of problematic real estate loan accounts in this analysis supports the contention of Cole and White (2012) that banks’ decisions to heavily invest in residential mortgage-backed securities (RMBS) have been singled out as one of the major triggers of the last recession. Other studies have also singled out real estate loan accommodations for their important role in predicting bank failure (Jin et al., 2011; Cole and White, 2012). On the other hand, as the banking industry’s consumer loan portfolio has grown in recent years, the quality of such loans was found to have a significant effect on the banks' probability of survival (El-Ghazaly and Gopalan, 2010).

Results also confirm the effectiveness of the loan portfolio diversification strategy. In this analysis, the HHI variable is significantly negative, which emphasizes the risk-reducing effect of the loan portfolio diversification strategy that ultimately increases the banks' survival probability. The positive and significant coefficient on PROFIT conforms to logical expectations. Higher earnings enhance the value of the banks' net worth and thus, greater wealth translates to greater financial strength and higher probability of survival.

Results also indicate that interest rate risk management and more appropriate fund sourcing strategies can enhance banks' chances of survival. The coefficient result for DEPLIAB is positive and significant, which is consistent with the expectation that the banks' capability to thrive in their businesses is enhanced by their ability to generate an adequate deposit base to meet their business funding requirements. The GAP variable that captures interest rate risk has a significantly negative effect on the probability of survival as higher GAP values are associated with higher interest rate risk.

The SIZE variable is significantly and negatively related to the probability of survival. For the banks observed in this sample, this result suggests that larger banks were more likely to fail during the last recession, which seems to disagree with Thomas (1991) ' "too big to fail" doctrine. Thomas (1991) argued in his study that endangered or at-risk larger financial institutions will tend to receive financial and other assistance from regulatory authorities because their failures are thought to impose severe repercussions to the economy. A cursory look at the profiles of the banks that failed in the last recession suggests that their median assets and deposits were considerably larger than non-failed banks (Aubuchon and Wheelock, 2010). Moreover, given that today's "more consolidated" banking industry consists of too many small institutions and very few large institutions (thus skewing the median asset-size downward), the Thomas doctrine hardly applies to the average bank observation and to this study's findings where banking units are not necessarily too large to have the industry effect the doctrine suggests.

3.4.2 Determinants of Temporal Endurance

The split-population model offers the advantage of being able to separate the factors that influence survival time from those that affect the probability of survival. This section analyzes the results for the vector of β coefficients that measure the influence of covariates on the bank's survival time. This analysis can also be labeled as temporal endurance analysis where the focus is on how certain factors can either expedite a bank's retrogression into failure or enhance the period of endurance of pressures to survive the financial crisis over time. In this case, a positive coefficient indicates that the covariate is associated with a longer duration time (or endurance over time), while a negative coefficient implies a more immediate incidence of failure.

Compared to the α parameters estimates where 9 regressors (exclude intercept) are statistically significant, 8 variables are significant in the β parameters model. Among these significant variables are those that were already identified as significant variables in the α model: consumer loans portfolio ratio (CONSUMLOANS), the loan risk or delinquency variables for real estate loans (REALESTNP), bank earnings (PROFIT), the banks' deposits to liabilities ratio (DEPLIAB), and bank size (SIZE). These variables also produced the same directional effects (coefficient signs) as those estimated for the probability of survival (α parameters).

Two other variables were previously insignificant in the probability model are significant in the β model for the determinants of survival time. The variable CINP has a significant negative coefficient in the β model, thereby suggesting that banks with higher accumulation of delinquent industrial loans may fail in a shorter time. Moreover, the variable INSIDER has a significantly positive relationship with survival time. Although seemingly counter-intuitive, this result may suggest that extending higher credit accommodation to the banks' management and owners may be regarded as an effective incentive strategy. Such incentives could have elicited the much needed loyalty and productivity that could help enhance their institutions' temporal endurance or extend the banks' survival time. On the other hand, this result could also reflect the confidence of insiders in their institutions' financial strength, perhaps derived from unobservable "insider" information on the banks' real conditions. Such confidence is translated to greater patronage of insiders' credit dealings with their own employer that could ultimately serve as a good signaling strategy directed to prospective investors and other market players.

One variable has contrasting coefficient sign results for the α and β models. The estimated coefficient of PURFUNDS, previously with a positive result in the α model, has a negative sign in the β model. The latter result indicates that banks that hold larger proportions of purchased liabilities obtained from national markets may have shorter survival periods as such purchases may have exerted some immediate liquidity pressures for the purchasing bank. However, on a medium- to long-term perspective, such transactions may prove to be strategic purchases for building up funding endowments to cover eventual needs to bolster liquidity and thus, would actually enhance a bank's chances of survival.

3.5 Conclusions and Implications

A split-population duration model developed by Schmidt and Witte (1989) is used in this study to examine the determinants of a bank's survival and temporal endurance. In contrast to the parametric duration model used in previous studies, the split-population model treats failed and survival banks differently by estimating an extra parameter, δ, which stands for the probability of bank's eventual failure. This study's results identify the isolated effects of certain variables on a bank's temporal endurance that have not been captured by other commonly used survival models. Such lapses in other duration models can understate the real determinants of a bank's probability of survival and its temporal endurance.

The most compelling result in this study is the insignificance of the delinquency measure for agricultural loan portfolios in both the survival probability and time models. This validates the true state of the farm lending industry in the late 2000s that refute the more pessimistic regard of experts and analysts on the farm sector. During the recession, agricultural lenders have, in fact, made cautious, prudent operating decisions as majority of them 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 (Ellinger and Sherrick, 2008). Moreover, data compiled and released by the Federal Reserve Bank show that while the entire 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 (Agricultural Finance Databook). The agricultural loan delinquency rates have consistently been below the banking industry's overall loan delinquency rates since the 1st quarter of 2004, and the gap has widened since then. On the other hand, agricultural production price and demand has been strong before the recession because of the combination of increased demand from developing countries, the falling value of the US dollar, and the growing importance of biofuels. These factors has boosted the agricultural economy and helped agricultural sector to weather the financial crisis.

This study presents an emphatic contention that while the agricultural sector has usually been regarded as a volatile sector potentially vulnerable in periods of economic crises, the commercial banks' dealings with farm clients during the late 2000s did not have significant adverse effects on the banks' financial health. Farm credit transactions in the last recession neither increased the commercial bank lenders' chances of failure nor expedited the deterioration of their financial conditions.

On the other hand, this study's results direct the attention to the banks' real estate, industrial, and consumer loan accommodations as delinquency rates for consumer and industrial loans adversely affected the banks' chances of survival and temporal endurance, respectively, while real estate loan delinquency rates have negative effects on both the probability of survival and temporal endurance. Important lessons and policy implications can be derived from the repercussions of such lending decisions. Recalling that the deterioration of the quality of real estate loan portfolios during the recession began when real estate prices started to decline in 2006, lenders should become more attentive to and more cautious about economic bubbles in the different industries they lend to. Notably, in the pre-recession period, real estate loan clients only were required by banks to put up around 20% to 30% equity infusion. The losses from unpaid real estate loans would have been minimized if only such requirement was set higher to around 50%, which banks now actually require. This argument further underscores the need for banks to closely monitor unsecured loan accommodations, especially their consumer loan portfolios that, according to latest statistics, have grown tremendously after the recessionary period (El-Ghazaly and Gopalan, 2010).

Even with the implementation of several federal programs designed to provide relief and assistance to surviving banks (such as the Federal Reserve's discount window, interest rate policies and other open market operations, among others), these institutions need to supplement such efforts with improved internal controls for better monitoring of performance efficiencies of various operating units, more protective loan covenants especially for unsecured or less secured loan transactions, more prudent business decisions (such as greater portfolio diversification, strategic liquidity-enhancing, and more practical asset expansion decisions), and greater caution in dealing with business opportunities in various sectors of the economy, including their clients in the farm industry.

Table 3.1. Definitions and Summary Statistics of Duration Model Variables

Variables	Descriptions	Sample Mean	Std. Deviation	Min	Max	Expected Sign: Survival	Expected Sign: Survival Time
Dependent variable							
T	Length of time between t=1 and the subsequent failure date T	20.4287	2.5599	1	21		
Explanatory variables							
AGLOANS	Agricultural loans / total loans	0.0772	0.1275	0	0.7636	+/-	+/-
CONSUMLOANS	Consumer loans/total loans	0.0775	0.0880	0	1.0000	+/-	+/-
CILOANS	Commercial & Industrial loans / total loans	0.1530	0.0988	0	0.9668	+/-	+/-
REALESTNP	Aggregate past due/non-accrual real estate loans/total loans	0.0142	0.0198	0	0.3597	-	-
AGNP	Aggregate past due/non-accrual agricultural loans/total loans	0.0007	0.0039	0	0.1597	-	-
CINP	Aggregate past due/non-accrual Commercial & Industrial loans /total loans	0.0008	0.0023	0	0.0549	-	-
CONSUMNP	Aggregate past due/non-accrual Consumer loans /total loans	0.0005	0.0023	0	0.0731	-	-
HHI	Herfindahl index constructed from the following loan classifications: real estate loans, loans to depository institutions, loans to individuals, commercial & industrial loans, and agricultural loans.	0.5606	0.1692	0	1.0000	-	-

Table 3. 1. Continued

Variables	**Descriptions**	**Sample Mean**	**Std. Deviation**	**Min**	**Max**	**Expected Sign**	
						Survival	**Survival Time**
PROFIT	Return on assets (Earnings)	0.0507	0.0481	-0.4452	0.4612	+	+
PURFUNDS	Purchased funds to total liabilities	0.5085	0.1398	0	0.9952	-	-
DEPLIAB	Total deposits/ total liabilities	0.9254	0.0866	0.00001	0.9996	+	+
GAP	Duration GAP measure [a]	-0.0403	0.2100	-2.1587	0.9468	-	-
OVERHEAD	Overhead costs/total assets	0.0211	0.0115	0	0.3747	-	-
INSIDER	Loans to insiders/total assets	0.0154	0.0181	0	0.1973	-	-
SIZE	Natural logarithm of total assets	11.8331	1.1820	8.1137	18.1842	+	+

[a] GAP = Rate sensitive assets – Rate sensitive liabilities + Small longer-term deposits.

Table 3.2. Maximum Likelihood Parameter Estimates [a] and Standard Errors [b] for Split-Population Duration Model

Variable	Label	Split-Population Model †			
		α Survival	P-value	β Survival time	P-value
Intercept		**7.4449 (1.5131)**	**<.0001**	**2.6189 (0.8027)**	**0.0006**
Ag loans	AGLOANS	0.1752 (0.1661)	0.1457	-0.0251 (0.1374)	0.4277
Consumer loans	CONSUMLOANS	**0.9304 (0.3255)**	**0.0021**	**0.3473 (0.2494)**	**0.0819**
C&I loans	CILOANS	-0.2342 (1.9150)	0.4513	0.9773 (0.9876)	0.1612
Real Estate Non-performing loan	REALESTNP	**-19.4559 (3.3798)**	**<.0001**	**-3.8449 (0.5384)**	**<.0001**
Ag Non-performing loan	AGNP	-0.2247 (0.4967)	0.3255	-0.3573 (0.3048)	0.1205
C&I Non-performing loan	CINP	-0.1779 (0.3792)	0.3195	**-0.4654 (0.1395)**	**0.0004**
Consumer Non-performing loan	CONSUMNP	**-0.9756 (0.6967)**	**0.0807**	-3.4148 (4.5155)	0.2248
Herfindahl Index	HHI	**-2.2766 (1.1865)**	**0.0275**	0.7827 (0.6772)	0.1239
Profit	PROFIT	**0.9073 (0.2257)**	**<.0001**	**0.3780 (0.1326)**	**0.0022**
Purchased Liabilities to total liabilities	PURFUNDS	**0.9182 (0.5646)**	**0.0520**	**-0.2812 (0.1926)**	**0.0721**
Deposits to liabilities	DEPLIAB	**1.6242 (0.8828)**	**0.0329**	**0.5275 (0.3693)**	**0.0766**
Duration GAP	GAP	**-0.4236 (0.0377)**	**<.0001**	0.0018 (0.0160)	0.4541
Overhead cost	OVERHEAD	0.3514 (0.7111)	0.3106	0.1548 (0.1531)	0.1560
Insider loan	INSIDER	-0.1262 (0.3572)	0.3620	**0.3133 (0.1793)**	**0.0403**
Size, log(total assets)	SIZE	**-0.4611 (0.0710)**	**<.0001**	**-0.1072 (0.0330)**	**0.0006**
	P	3.8894 (0.2468)	<.0001		

† Log likelihood at convergence is: -2032.6016, convergence criterion achieved is: 0.0100

[a] Results in boldface are significant at least at the 90% confidence level.

[b] Number in parentheses is the estimate's standard error.

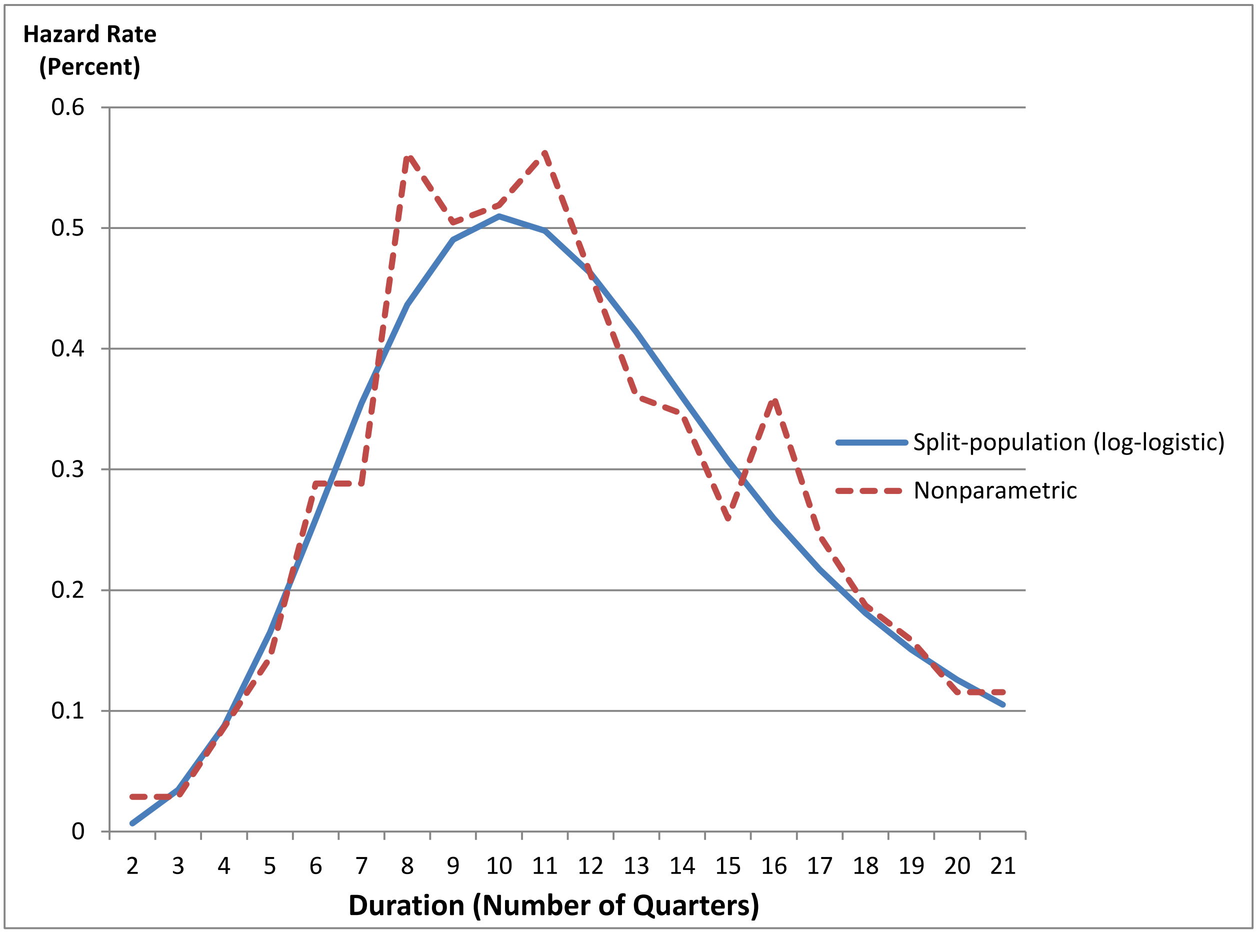

Figure 3.1. Estimated Hazard Rate for Bank Failure, 2008 Q1-2012 Q4

CHAPTER 4

Changes in the Farm Loan Borrowers' Credit Risk Profile during the Recession: The Application of the Transition Probability Model to Gender and Racial Borrower Groups of the Farm Service Agency Lending Programs

4.1 Introduction

Federal involvement in farm credit is guided by the government's mission to assist under-served sectors of the farm economy experiencing difficulty in gaining access to borrowing funds through the regular lending channels. These borrowers include small, beginning farmers considered as high risk borrowers by commercial lenders due to their inadequate business track records and inferior net worth positions. Moreover, the federal credit program is also designed to accommodate borrowers who have been subjected to racial, ethnic or gender prejudice by other lenders.

The implementation of federal lending programs, however, is constrained by the free market principle. The potential disruption of credit market conditions due to the availability of subsidized low-cost federal credit creates the need to regulate the delivery of federal farm loans. Hence, the government, instead of directly competing in the credit market, can only assume the role of "lender of last resort" specifically for farmers who have had experienced denials of their loan request from commercial lenders.

Today, one avenue the federal government uses to provide credit to farmers is through the Farm Service Agency (FSA) operating under the U. S. Department of Agriculture (USDA), which implements direct and guaranteed loan programs as temporary sources of credit for farm businesses. The mission of FSA is to fill the gaps in the commercial credit market in which creditworthy farmers, especially high-risk borrowers, are unable to obtain credit from a bank, cooperative Farm Credit System, or other agricultural lenders. Those farmers who have been facing credit issues are mostly beginning farmers that have insufficient financial resources and established farmers who may have experienced financial hardship. Young and new farmers are usually deficient in business track records and credit histories that regular lenders put a high premium on in their credit risk assessment models. Moreover, FSA is expected to ensure that socially disadvantaged borrowers belonging to racial and gender minority groups are given fair access to credit needed to sustain their farm business operations.

FSA's loan programs are specially designed to facilitate the progression or maturation of their high risk borrowers. First, their direct loan program should provide the funds needed by farmers to jumpstart their businesses. Direct loan borrowers are expected to eventually transition or graduate to the Guaranteed Loan Program where the farm borrowers can now deal with regular lenders for their credit needs through FSA's guarantee of their credit obligations. Other direct farm borrowers' businesses can mature at a much faster rate that these can even bypass the guaranteed loan stage and move on directly to a direct relationship with the regular lenders.

Given the relatively high risk profile of FSA's direct loan clients, it is important to investigate on how these borrowers have fared during periods of high economic volatility and uncertainty. During the late 2000s recession, there was a surge in bank failures as the quality of the banks' loan portfolios deteriorated rapidly. Under this backdrop, an analysis of changes or movements in the quality of FSA's high risk direct loan borrowers would provide interesting and important implications for operating strategy and policy modification purposes. Credit risk migration techniques will be used to analyze changes in FSA's borrower quality during the recession.

Credit risk migration analyzes the likelihood that a borrower will remain in the same risk rating category from one period to the next. Deterioration in credit quality by migration to a higher risk category is termed as a credit downgrade and an improvement is considered a credit upgrade, while remaining in the same class is defined as retention. These migration rates are used to capture and ascertain the credit quality of lenders' loan portfolios according to class upgrades versus downgrades, and derive estimates of probability of loan default or stress rates.

This study is designed to address three goals. First, the analysis will employ two "Markov Chain" approaches: time homogeneous and non-homogenous models to estimate credit migration rates of FSA's direct loan borrowers from 2005-2012. The estimated transition matrices will be used to compare the results from those calculated using the more basic discrete time approach.The second goal is to compare the transition rates between social categories of farm borrowers, namely female farmers and male farmers, white farmers and non-white farmers[8]. It is believed that economic shocks, such as the most recent economic recession, can affect female and non-white farmer groups differently given the inherent variations in structural attributes, infrastructural support, resource endowments, and varying levels of opportunities and access to sources of assistance and resources that may be results of longitudinal, historical events that created such inequities.The third goal is to identify factors that could influence the volatility of the farm borrowers' migration rates. Several variables will be used to capture demographic, farm financial, and structural attributes, that capture the farm borrowers' inherent characteristics. In addition, external variables such as key macroeconomic factors are also considered to evaluate their effects

[8] Non-white farms include African American, Asian/Pacific Islander, American Indian, and Hispanic.

on the changing quality of FSA's direct loan borrowers. It is expected that some types of farms are more vulnerable to the economic downturns than others.

4.2 Literature Review

Credit migration or transition measures the probability of upgrade and downgrade from an existing credit rating. Standard and Poor's, Moody's ratings, and Fitch Ratings are the most widely accepted rating agencies that routinely assess the financial status of companies, as well as the analysis of the changing quality of bonds and other publicly traded securities. A simple application of this technique was used to evaluate a bond or loan portfolio. However, as credit rating information has become more vital in investors and commercial lenders' decisions, more sophisticated risk management tools were developed, and credit transition matrices became cardinal inputs in various applications of risk management. For example, the input from transition matrices would be used in the development of complex structured finance products, such as collateralized debt obligations and credit default swaps, as well as other complex derivative and portfolio management products (Violi, 2004). Meanwhile, credit ratings analysis has acquired new roles in the New Basel Accord since it is essential to the credit risk component of capital management.

One major application of credit migration is to build default models. A simple default model utilizes historical ratings as major inputs to calibrate the migration frequencies between different ratings. To use a credit transition matrix as default model, previous studies typically used the last column of the matrix, which indicates the probability of default, and ascribe them to the corresponding rating classes (Fathi and Nader, 2007). However, one shortcoming of using transition matrices as a default model is that it is not dynamic. The model is based on long-term empirical probabilities of rating transitions, and therefore not sensitive to business cycles or other fluctuations in the economy.

Compared to its extensive practice in the financial industry, the concept of credit migration matrices on farm business lending is relatively new and unexplored. Unlike financial institutions, farm equity or capital is not traded and therefore not rated by those rating agencies. Instead, agricultural lenders usually use a credit scoring approach to assign loan borrowers into different rating categories (Splett et al, 1994). Barry, Escalante and Ellinger (2002) adopted the classification from Splett et al (1994) and applied the migration concepts to study the migration rates of farmers' credit scores using several time horizons and different credit classification variables. Phillips and Katchova (2004) examined the credit score migration rates of farm businesses and tested the dependence between migration rate and business cycles. Their results revealed that farmers' credit ratings exhibit a higher tendency towards being downgraded during the recession, while there is a higher probability of upgrades in expansion. Katchova and Barry (2005) developed a credit risk model in order to estimate the capital requirement for agricultural lenders under the New Basel Capital Accord. Both the CreditMetrics and Moody's KMV models were used to estimate the capital needed for different risk classes, where CreditMetrics directly used the concepts of migration matrix to calculate the probability of default. Escalante et al. (2004) extended their application of the credit transition matrix paradigm by employing an ordered logit regression on a panel level farm business data to discern the determinants of changes in credit quality captured by the transition probability measures. Most of the farm-specific factors used in their model did not produce any significant results while certain macroeconomic variables have shown significant impact on either the probability of upgrade or downgrade.

Large corporate rating agencies and most of the academic studies used discrete time (cohort) approach to calculate their transitions matrices (Lando and Skodeberg, 2002; Schuermann and Jafry, 2003). However, this cohort approach ignores any rating changes within sub-periods of a given time frame and focuses only on migration observed between the beginning and the end of a time period. The omission of such information on transient changes in the borrowers' credit risk quality between the two time end points would reduce the reliability of those cohort approaches in consistently producing accurate and efficient estimates of migration rates (Lando and Skodeberg, 2002).

To address the deficiency of the cohort method, a continuous time method under the Markov chain model was introduced based on modern survival analysis (Skodeberg, 1998). Lando and Skodeberg (2002) in their study proposed two different continuous time Markov chain models: time homogeneous and time non-homogenous, to estimate the transition probabilities and compare them to the results obtained from cohort method. A major rationale behind using continuous time model to replace discrete model is to estimate the true probability of a rare event. For example, for a given time period, if there is a transition from bond rating class AAA to AA by one firm, and AA to Default by another firm in the same period, the probability of AAA to default should not be zero, even if there has been no direct transition between AAA and default. Traditional cohort method will ignore the intermediate transitions and underestimate the true probabilities, while the two continuous Markov models will provide more accurate estimations. A study by Deng et al. (2007) also proved the relative strengths of the Markov chain models and showed their applications on farm level data. The study's results confirm that the cohort approach understated transition probability rates by producing lower indicators of farm loan portfolio quality, especially portfolio default probability estimates.

4.3 Methodology

The cohort method calculates migration rates under a discrete-time framework. Migration rates are calculated over a specific time period Δt by considering there are N_i number of firms in a given rating category i at the beginning of the time horizon, and out of this population N_{ij} number of firms have migrated to the category j, so the corresponding probability of migrating from category i to j over Δt is:

(4.1) $$P_{ij}^{\Delta t} = \frac{N_{ij}}{N_i}.$$

However, a Markov process is a sequence of random variables $\{X_{t+1} \mid t = 0,1,2,...\}$ with space S whose distribution satisfies

(4.2) $$\Pr\{X_{t+1} \in A \mid X_t, X_{t-1}, X_{t-2}, ...\} = \Pr\{X_{t+1} \in A\} A \subset S.$$

In this process a movement from one state to another is dependent only on what happened in the previous n states. The distribution of X_{t+1} conditional on the history of the process through time t is completely determined by X_t and is independent of the realization of process prior to time t. So the transition probabilities are indeed:

(4.3) $$P_{ij} = \Pr\{X_{t+1} = j \mid X_t = i\} i, j \in S.$$

4.3.1 The Time Homogeneous Markov Chain Model

Consider a K-state Markov chain where state 1 is the highest rating category and state K is the default rate. We collect the transition probabilities of the Markov chain for a given time horizon through a K $\times$ matrix $P(t)$ whose ij_{th}'s element is the probability of migrating from state i to state j in a time period of t. This continuous-time chain *generator* matrix Λ can be presented as a K $\times$ K matrix for which

(4.4) $$P(\mathrm{t}) = \exp(\Lambda\,\mathrm{t}) \cong \sum_{k=0}^{\infty} \frac{\Lambda^k t^k}{k!}, \quad t \geq 0.$$

where Λt is the matrix Λ multiplied by t on every entry and the exponential function is a matrix exponential approximated by the infinite summation defined by the most right-hand side expression. Hence, one can obtain the maximum likelihood estimators of the transition probability matrices by obtaining the maximum likelihood estimator of this generator first and then applying the matrix exponential function on this estimate, scaled by time horizon.

The entries of the generator Λ satisfy

(4.5) $$\begin{aligned} &\lambda_{ij} \geq 0 \quad for \quad i \neq j \\ &\lambda_{ii} = -\sum_{i \neq j} \lambda_{ij} \end{aligned}$$

which guarantees that sum of the rows of the matrix is equal to one. The parameter λ_i is defined as the probabilistic behavior of the holding time in state i, where $\lambda_i = -\lambda_{ii}$, and the probability of jumping from state i to j given a jumping occurs is defined by λ_{ij} / λ_i .

To estimate the generator matrix Λ we need to obtain the estimates of its entries. The maximum likelihood estimator of λ_{ij} is given by

(4.6) $$\lambda_{ij} = \frac{N_{ij}(\mathrm{T})}{\int_0^T Y_i(\mathrm{s})\,\mathrm{ds}}$$

where $N_{ij}(\mathrm{T})$ is the total number of transitions over the period from i to j , and $Y_i(\mathrm{s})$ is the number of farms assigned credit category i at time s. The interpretation of this equation is: numerator counts the number of observed transition from i to j over the entire period of observation, and the denominator effectively collects all observations assigned with category i over period T. Thus, any period spent in a particular rating class will be picked up in the denominator.

In the case of farm credit assignment, suppose a farm spent a portion of time period T in transit from class 1 to 2 before eventually downgrade to 3 at the end of time T. The time spent in class 2 will be captured by this design and factored into the estimation of the transition rates for classes 1 to 3. Previously used cohort method ignored this "transient" migration information.

4.3.2 The Time Non-Homogeneous Markov Chain Model

Time homogeneity is a useful assumption in estimating a one-year transition matrix, however, may not be suitable for a long run estimation period. Therefore, a non-parametric non-homogeneous Markov chain approach is developed to better fit transition probability matrix for the period from time s to time t given by $P(\mathrm{s},\mathrm{t})$:

(4.7) $$\hat{P}(\mathrm{s},\mathrm{t}) = \prod_{k=1}^{m} (\mathrm{I} + \Delta\hat{A}(\mathrm{T}_k))$$

where T_k is a jump in the time interval from s to t. The matrix component of the above equation is constructed as follows:

(4.8) $$\Delta A(\mathrm{T}_k) = \begin{bmatrix} -\frac{\Delta N_{1\bullet}(\mathrm{T}_k)}{Y_1(\mathrm{T}_k)} & \frac{\Delta N_{12}(\mathrm{T}_k)}{Y_1(\mathrm{T}_k)} & \frac{\Delta N_{13}(\mathrm{T}_k)}{Y_1(\mathrm{T}_k)} & \cdots & \frac{\Delta N_{1p}(\mathrm{T}_k)}{Y_1(\mathrm{T}_k)} \\ \frac{\Delta N_{21}(\mathrm{T}_k)}{Y_2(\mathrm{T}_k)} & -\frac{\Delta N_{2\bullet}(\mathrm{T}_k)}{Y_2(\mathrm{T}_k)} & \frac{\Delta N_{23}(\mathrm{T}_k)}{Y_2(\mathrm{T}_k)} & \cdots & \frac{\Delta N_{2p}(\mathrm{T}_k)}{Y_2(\mathrm{T}_k)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\Delta N_{p1}(\mathrm{T}_k)}{Y_p(\mathrm{T}_k)} & \frac{\Delta N_{p2}(\mathrm{T}_k)}{Y_p(\mathrm{T}_k)} & \frac{\Delta N_{p3}(\mathrm{T}_k)}{Y_p(\mathrm{T}_k)} & \cdots & -\frac{\Delta N_{p\bullet}(\mathrm{T}_k)}{Y_p(\mathrm{T}_k)} \end{bmatrix}$$

The numerator of each off-diagonal element, $\Delta N_{ij}(\mathrm{T}_k)$, denotes the number of specific transitions moving away from state i to some other state j at time T_k . The numerator of the diagonal elements, $\Delta N_{i\bullet}(\mathrm{T}_k)$, is the total number of transitions away from state i at time T_k . $Y_i(\mathrm{T}_k)$ is the number of farms in state i right before time T_k . Hence, the diagonal elements in row i count the fraction of the exposed farms $Y_i(\mathrm{T}_k)$ which leaves the state at date T_k , regardless of which state they migrated to. And off-diagonal elements count the specific types of transitions away from the state divided by the number of exposed farms. Note that the sum of the rows of the matrix $I + \Delta\hat{A}(\mathrm{T}_i)$ in equation (7) is equal to one. Moreover, when there is only on transition between time s and t, the resulting estimator (7) collapses the non-homogenous transition matrix into a cohort matrix.

4.3.3 Comparing Different Transition Matrices

This study has presented three different methods for estimating the entries in the credit migration matrix. To further understand the similarities and differences within different categories, the three methods were also applied to each individual group. Therefore, total 15 different transitions matrices were generated in this study. In order to compare these different matrices and evaluate how significant different they are from one to another, we applied the Singular Value Decompositions (SVD) analysis. Following Jafry and Schuermann (2003), the singular values is denoted as $S(\tilde{P})$ of $\tilde{P}$, a mobility matrix (defined as the original matrix minus the identity matrix).

The singular value is computed using:

$$S(\tilde{P}) = \sqrt{eig(\tilde{P}'\tilde{P})} \qquad (4.9)$$

Since the numbers of eigenvalues is consistent with the matrix dimension, the average of the singular values are computed as $\overline{S(\tilde{P})}$.

These singular values which are calculated from the Cohort method, and two Markov Chain Models (Time Homogeneous, Time Non-Homogeneous) are labeled as $\overline{S(\tilde{P}^{C})}$, $\overline{S(\tilde{P}^{TH})}$, and $\overline{S(\tilde{P}^{TNH})}$, respectively. Then, the pairwise differences between the $\overline{S(\tilde{P})}$s, take cohort and time homogenous for example, would be calculated as:

(4.10) $$m_{svd}(\tilde{P}^{C}, \tilde{P}^{TH}) = \overline{S(\tilde{P}^{C})} - \overline{S(\tilde{P}^{TH})} \ .$$

To determine the significant difference between two matrices, we need to compute the significant level based on statistical test. However, the distributional properties of $m_{svd}(\tilde{P}^{C}, \tilde{P}^{TH})$ is unknown, and we cannot use any statistical test which assumes certain distributions. One efficient way to bypass this difficulty is through the resampling technique of bootstrapping (Jafry and Schureman, 2003).

In this study, we randomly draw 2000 farms with replacement from the entire sample, and create 500 bootstrap samples, which will give us 500 different singular values $m_{svd}{}^{(K)}$, where K=1,2, …, 500. Based on the distribution of these 500 singular values, we can set up a critical value α (e.g. α =5%), and find out the 1-α confidence interval of this distribution. If there are 0 fails within this confidence interval, we conclude that the two matrices are not significant different from each other under 5% level.

4.3.4 Ordered Logistic Regression

An ordered logistic regression technique is used in this study, given the ordinal nature of credit ratings and rating changes. Ordered probit/logit approach has been widely used in different credit rating studies and is shown to be more appropriate than the regular OLS model in analyzing this issue (Trevino and Thomas, 2001; Bissoondoyal-Bheenick, 2005).

Given the random effects ordered logit model defined as follow:

(4.11) $$y^*_{it} = \alpha + V_{it}'\beta 1 + W_{it}'\beta 2 + u_i + \varepsilon_{it}$$

where y^*_{it} is an unobserved latent variable linked to the observed ordinal response variable y_{it}, which are defined as

$$y_{it} = \begin{cases} 0, \text{ if experienced downgrades} \\ 1, \text{ if experienced retentions} \\ 2, \text{ if experienced upgrades} \end{cases}$$

and

$$y_{it} = \begin{bmatrix} 0, & \text{if } y^*_{it} \le \mu_1 \\ 1, & \text{if } \mu_1 < y^*_{it} \le \mu_2 \\ 2, & \text{if } \mu_3 < y^*_{it} \end{bmatrix}.$$

$\mu_i s$ are unknown parameters that needs to be estimated using maximum likelihood estimation. V_{it} represents structural/demographic farm level variables, and W_{it} are variables related to macroeconomic factors. u_i is an unobserved, time-invariant, individual-specific heterogeneity (random effect) and ε_{it} is a white noise error terms that follows zero means and constant variance. Define $\omega_{it} = u_{it} + \varepsilon_{it}$, we have the following features under random effect assumptions:

(4.12) $$Cov(u_{it}, \varepsilon_{it}) = 0$$

(4.13) $$Var(\omega_{it}) = \sigma_u^2 + \sigma_\varepsilon^2$$

(4.14) $$\rho = Corr(\omega_{it}, \omega_{is}) = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\varepsilon^2}, t \neq s$$

where ρ is the proportion of the panel-level variance component to the total residual variance (Greene, 2012).

4.4 Data

This study utilizes the borrower-level Farm Business Plan data from the Farm Service Agency (FSA) national office spanning from 2004 to 2013. The data set contains the loan level information such as balance sheet, income statement, cash flow, and production history. Access to such extensive national database is covered by a Memorandum of Agreement (MOA) between this institution and the Farm Service Agency (FSA) of the U.S. Department of Agriculture (USDA).

The Farm Business Plan data is updated when a credit action is undertaken such as the filing of an application for a new loan or the restructuring of outstanding loans. However, if the action was taken within a year, a farm’s balance sheet and income statement will not change significantly and, thus, will also receive the same credit score given their financial information. A usual time frame used by either financial institutions or rating agencies is one year. In order to make it consistent with industry standard and simplify the migration movements, the farm level data was converted to annual level, which means that if there are multiple loan actions that happened in the same year, only one record will be used (If the financial information and credit ratings are different within a given year, the average values of those information are kept in the annual level data). Therefore, after removing the duplications and any farm with missing identification numbers, there are total of 61,007 farms in the Business Plan data set, and the yearly distribution of those farms are summarized in table 4.1. In order to determine whether there are distinct differences in the credit migration patterns caused by demographic attributes, the data is further disaggregated into sub-groups of operators belonging to the Female, Male, White, and non-white categories using gender and racial identification code in the data.

Instead of adopting a uniform credit-scoring system which has been used in previous studies (Splett et al 1994; Barry, Escalante, and Ellinger, 2002; Xiaohui et al, 2007), this study directly used credit risk classification variable from FSA's borrower account classification system. As shown in table 4.2, a weighted percentage of the score for each of the 4 measures of financial performance and operation stability (current ratio, debt to asset ratio, return on asset ratio, term debt and capital lease coverage ratio (TDCLC)) is used to calculate the total overall score. FSA rates borrowers using a classification system from 1 to 4 with 1 being the best and 4 being the highest risk. These categories are: 1= Commercial; 2=Standard; 3=Acceptable; 4=Marginal.

In corporate finance studies, ratings for loans might be categorized into "Not Rated" or "Withdrawn rating" if the debt expired, the debt is called, or the borrower fails to pay the requisite fee to the rating agency (Violi, 2004). There is no "WR" or "NR" class in FSA's credit ratings; however, farm numbers vary by year and some farms may re-join the program after its early "graduation". To control for the changes in the number of farms, all farms that joined the program are classified into "NR" class if their records are missing in a given year. Later on, we treat the NR classification as non-informative as generally used by industry (Schuermann and Jafry, 2003; Violi, 2004) and the probability of transitions to NR is distributed equally among all other states.

In order to conduct a more in-depth analysis of the factors that could influence the volatility of migration rates among different farms, this paper follows Escalante et al (2004)'s research in applying an ordered logistic model to study the determinants from farm demographic and structural variables, in addition to macroeconomic variables. The ordered logit model will utilize a balanced panel level data that only include those farms that consistently maintained records from 2005 to 2012. Farm demographic and structural variables are directly collected from Farm Business Plan data. To study how macroeconomic variables affect the rating migration trend, state-level and national level macro-variables were mapped to the data using farms' geographic information. Aggregate national-level and state-level macroeconomic indicators were collected from Federal Reserve Bank of St. Louis and Bureau of Economic Analysis (BEA). Farm production and farm land values are collected from the U.S. and State Farm Income and Wealth Statistics datasets from U.S. Department of Agriculture (USDA).

4.5 Results

4.5.1 Credit Migration Matrices

The financial industry usually evaluates lenders' behavior on a quarterly basis where the Markov Chain Model finds more relevance as it is designed to take into account the intermediate transition ratings. However, as mentioned in the Data Description section, farms in this sample were only evaluated for their credit rating when a credit action is undertaken. The frequency of the rating evaluation varies across different farms for different years. In addition, a farm's financial conditions usually stay the same in the same year, such that restricting the time interval of migration matrices to a time frame less than one year would result in higher retention rates. Therefore, we cannot simply apply the common migration interval (one year) used by corporate finance study.

On the other hand, if we were using a one year 1×1 transition matrix, there would be no intermediate ratings that may be omitted since the data is converted to annual level, and would result in identical matrices under the cohort method and non-homogeneous method (Xiaohui et al, 2004). To resolve this issue, we adapted a biannual transition matrix that computes the migration under a two-year horizon. For example, credit ratings will only be evaluated at the beginning of first year and end of third year, while ratings in second year were omitted. In this case, there is only one discrete transition from the first year to the third year, and time continuous models will capture two transitions within these three-year period. Given the time frame from 2004 to 2013, this biannual method would result in eight migration matrices, with each matrix constructed from data on three consecutive years.

Table 4.3 presents 95% confidence interval for the pairwise differences of different transition models. The confidence intervals are calculated based on 500 bootstrapped samples (2,000 farms are randomly selected for each draw). Transitions matrices calculated using cohort, time homogeneous, and non-homogeneous are all significantly different from each other across different categories. Table 4.4 further compares the matrices between different categories. In the case of the Cohort method for instance, the resulting 95% confidence interval for the difference is (0.0046, 0.0097) for Female vs. Male Farm, and the difference is (-0.0056, -0.0005) for White vs. Non-White Farm. Both of these intervals do not include zeros. These results indicate that the transition probabilities are significantly different between different categories. The confidence intervals only include zeros when comparing All Farms to Male, and All Farms to White Farm. However, since the entire sample contains 84% of male farmers and 93% of white farmers, it is not surprising to see that their transition matrices are not significantly different from those calculated using the whole sample.

Table 4.5 compares three different transition matrices using the entire farm sample. Consistent with the findings of previous empirical studies (Lando and Skodeberg, 2002; Deng et al, 2003), the cohort method generates the lowest transition rates under the extreme credit class transitions (from class 1 to class 4 and vice versa). For example, the transition probability from class 1 to class 4 is 12.21 percent under time homogeneous and 13.40 under time non-homogeneous, while the cohort method has under-estimated the rare case transitions since it does not capture the transient migration. On the other hand, the non-homogeneous matrix is designed to relax the time homogenous assumption in the long run. Therefore, the results from the non-homogeneous method can more closely capture the true transition rate in a 10 year time frame.

The transition probabilities calculated for male farm borrowers seem to dominate those estimated for female borrowers, especially in terms of retentions rates (diagonal terms) and upgrades (rates below the diagonal terms) (Table 4.6-4.7). This is especially true when the two Markov chain models are considered. The probability of downgrade for male farms ranges from 12.04% to 25.71% under time-homogeneous model, while the probability of downgrade for female farms under the same model is 16.33% to 27.08%. When using time non-homogeneous model, there are 17.66% of female farms downgrade from class 1 to class 4, but only 13.21% of male farms experience the downgrade between these two classes.

Comparing the time homogeneous migration matrices of white and non-white farm borrowers for all ratings, the white borrowers' matrix reflected higher retention rates while the non-white borrowers' matrix tend to have higher rates of downgrade (Table 4.8-4.9). Take time homogeneous model for instance, the average retention rate for white farm borrowers is 43.06%, while non-white farm borrowers have retention rate of 42.16%. Under time homogeneous model, white farms have probability of downgrade ranging from 11.88% to 25.67%, while non-white farms have higher downgrade interval which ranges from 17.80% to 29%. When comparing the probabilities under time non-homogeneous model, the worst case downgrade (from class 1 to class 4) for white farms is 13.10%, but for non-white farms is 19.24%.

4.5.2 Determinants of macroeconomic variables on the probability of upgrade and downgrade

Ordered logistic regression can be estimated in a situation when the discrete dependent variable has more than one categories and the values of each category have a meaningful sequential order. In this study, the rating classification have four classes and can be furthered aggregated into “Upgrade”, “Retention”, and “Downgrade”. Therefore, ordered logit model is an appropriate method to evaluate the determinants that could affect the probability of credit rating transitions.

The list of independent variables includes both farm level information and macroeconomic variables, measured either at the state or national level. Since most of the financial variables in the data have been used as inputs to calculate the credit rating, the possibility of potential endogeneity is minimized by including only the asset turnover ratio, which is calculated from gross revenue divided by total assets, farm size (natural log of total assets). The farm borrower’s age at the time of the initial credit rating was assigned. Several macroeconomic variables (such as GDP, State level per capita income) were removed due to the concern of multicollinearity.

Table 4.10 presents the final model with the variables’ coefficients and z-statistics. Dependent variable is ordered from incidences of a downgrade (Y=0) to an upgrade (Y=2). Therefore, a positive coefficient would indicate that an increase in a certain explanatory variable would result in an increase in the probability of credit migration upgrade, while a negative coefficient would suggest an increase the probability of downgrade. Overall, six out of nine variables are significant under at least 10% level in the model.

4.5.2.1 Farm Structural and Financial Variables

For the three farm financial variables, only farm size and age are significant under the 5% confidence level. Farm size is positive and significantly correlated to the probability of upgrade, which indicates that an increase in farm size would lead to an increase in credit ratings. Larger farms have greater economies of scale and production efficiencies compared to the smaller sized farm. It is expected that smaller farms are more vulnerable during economic recession. Farm owner's age was recorded at the date a credit action was taken. Young and beginning farmers usually have less experience in operating a farm and have lower credit rating when starting their business. A positive sign for farmer's age is expected since age is correlated with farmer's experience.

4.5.2.2 Macroeconomic Determinants

Percentage change in S&P 500 index is included as proxy for the overall performance of stock market. Improvement in stock market can be seen as a sign of economic recovery, and this variable should have a positive impact on the probability of upgrade. However, it is significant but shows a negative sign.

Money supply measures the level of safe assets that businesses can use to make payments or to hold as short-term investments. Tighter money supply conditions could cause an upward pressure on the lending cost for farmers, since they had to borrow from banks annually in order to plant cash crops and can only make repayment at harvest time. Increased growth rate in money supply would relax their credit availability constraint and allow them to make investments to improve their profitability. Therefore, a positive sign is consistent with our expectation.

The percentage change in state level income has positive and significant impact on the probability of upgrade. Increase in income would increase people's ability in purchasing farm products, thereby increasing the probability of an upgrade.

Livestock growth rate is a measurement directly related to farm's performance. This variable is significant and positively related to the probability of upgrade, as attributed to improvement in the farm's financial conditions attributed to its livestock operations[9].

To further explore the direction of each variable's impacts, marginal effects of the significant regressors were calculated and reported in table 4.11. The marginal effect provides more intuitive information on the effect of each unit change in the value of the variable on the probability of upgrade and down grade.

Between the two structural and demographic variables, the probability of downgrade/upgrade is more sensitive to the unit changes in Size than to similar increments in borrower's age. For instance, a one-year age increase would only increase the probability of upgrade by 0.0006, while one unit change in farm size would increase the probability by 0.0127.

Money supply and state level per capital income changes both have negative and positive marginal effects on the probability of downgrade and upgrade, respectively. A unit change in money supply increase the likelihood of upgrade by 0.0055. Growth rate of state level income, on the other hand, increases the likelihood of upgrade by 0.0044.

Livestock production growth rate has the highest marginal effect among the significant independent variables. A unit increase in the growth rate would results in a 0.2002 percentage

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[9] Crop production growth rate was first considered as a direct measurement related to farm's performance. However, this variable is not significant when combined with other macroeconomic variables.

change in the probability of upgrade. However, it would also increase the probability of downgrade by a fair amount when it was decreased. The marginal effects indicate that a unit decrease in growth rate would increase the likelihood of upgrade by 0.1857.

4.6 Conclusion

USDA's Farm Service Agency (FSA) is considered a lender of last resort since it makes direct loans to those farmers who are unable to obtain credit from regular commercial lenders. Through financing farm production and farm real estate, this lending program is designed to be a transitional credit program for farmers who may have experienced financial hardship. Farmers receiving direct loans are expected to transition to commercial credit over time. To improve both the efficiency and effectiveness of this program, it is important to construct a study to identify borrowers who are likely to experience repayment problems, and therefore enable any implementation of proactive policies to reduce program losses.

This study is designed to identify borrowers that are either potentially or actually deficient in their loan obligations to the FSA through the evaluation of credit rating transitions among national-level farm borrowers using FSA's account level data. Three different credit migration matrices approaches (the standard discrete "cohort" method, and two continuous Markov Chain models) are used to calculate the probability of farm credit migrations from 2004 to 2013. To further explore the reasons behind credit transitions, a random-effects ordered logistic model is used to identify and quantify the effects of farm structural/demographic factors and macroeconomic factors that influence the probability of credit upgrade or downgrade.

Previous literatures compared the usual "cohort" method to two Markov Chains (Lando and Skodeberg, 2002; Schuermann and Jafry, 2004; Xiaohui, et al, 2007) for estimating credit transition probabilities. Consistent with their findings, this study also shows that the cohort method under-estimates transition probability rates, especially in extreme cases of transition such as when a borrower's credit rating is degraded from the top to the bottom rating. Significant differences were found when using singular value decomposition (SVD) to compare the migration matrices calculated from different models. These results suggest that the industrial standard "cohort" method will ignore the indirect, "transient" transition probabilities and thereby produce unreliable results.

The transition probability estimates establish that among the gender and racial classes of FSA loan clientele, female and non-white farm borrowers tend to display a greater need for financial assistance given their higher financial vulnerability (as may be reflected by higher rates of credit downgrade).

The number of female-operated farms nearly tripled from 1978 to 2007, up from 5 percent to nearly 14 percent (USDA, 2013). According to the latest agriculture census (2012), farms operated by female farmers account for 30% of U.S. farms (30% of all operators and 14% of principal operators). However, female farmers usually have limited access to funds, which may cause financial stress and leads to their farms being much less productive than those operated by men (Reynolds, 2008). Our results indicate that the female farmers' credit issues have prevented them from successfully migrating to a higher rating class. Therefore, policymakers should ensure that female farmers are allocated with sufficient funds even if their financial conditions may be less competitive in their respective borrower categories.

The same situation also applies to non-white farmers. Non-white farmers increased by nearly 15% since 2007 (2012 Agriculture Census). However, around 80% of the African American operated very small farms. As highlighted in the ordered logit regression, economies of scales (farm size) played an important role in increasing the probability of a credit rating upgrade. Large farms have greater capability in enduring economic hardships and have more efficient production systems and operations. The small business nature of farms operated by non-white classes makes them more vulnerable to financial volatility. It is important for FSA to carefully track their financial performance during the recession and provide additional assistance in helping their credit transitions.

In addition, ordered logistic results revealed that older and more experienced farmers are more likely to experience upgrade in ratings. Those farmers may be usually considered as preferred borrowers by creditors since they have already accumulated good credit and have good experience in operating more profitable business operations. On the other hand, young and beginning farmers are less likely to experience credit upgrades due to their lack of experience in farming and poor credit conditions.

Macroeconomic determinants such as money supply and income growth rate have provided the linkage between farmer's credit ratings and general economic environment. Even though agricultural production is not directly affected by the recent recession, the volatile and more challenging economic conditions have decreased the farm borrowers' probability of upgrade, thereby postponing the envisioned transition to commercial credit. FSA should monitor their borrowers' performance during the recession, and to implement support programs that will facilitate greater ease of their borrowers' transition through increasing funding support.

Table 4.1. Number of Farms from 2004 to 2013

Year	Number of Farms
2003	2
2004	4500
2005	20086
2006	25638
2007	25713
2008	26274
2009	27698
2010	29128
2011	29381
2012	26064
2013	21073

Table 4.2. Farm Credit Classification

Total Overall Score	**Classification**	**Classification Category**
1 to 1.59	1	Commercial
1.6 to 2.19	2	Standard
2.2 to 2.79	3	Acceptable
2.8 to 4	4	Marginal

Source: FSA Handbook, General Program Administration, 1-FLP

Table 4.3. Bootstrapped SVDs: Compare Different Transition Matrices

	95% Confidence Interval from Bootstrapped Sample		
	Cohort vs. Time Homogeneous	Cohort vs. Time Non-Homogeneous	Time Homogeneous vs. Time Non-Homogeneous
Whole Sample	**(0.0306, 0.0344)**	**(0.0758, 0.0797)**	**(0.0450, 0.0455)**
Female Farmer	**(-0.0342,-0.0307)**	**(-0.0234, -0.0197)**	**(0.0106, 0.0113)**
Male Farmer	**(0.0302, 0.0342)**	**(0.0755, 0.0794)**	**(0.0450, 0.0455)**
White Farmer	**(0.0318, 0.0358)**	**(0.0772, 0.0811)**	**(0.0452, 0.0456)**
Non-White Farmer	**(-0.0513, -0.0478)**	**(-0.0425, -0.0389)**	**(0.0084, 0.0092)**

Bold number indicates p-value < 0.05 (95% Confidence Interval)

Table 4.4. Bootstrapped SVDs: Compare Transition Matrices across Different Categories

	95% Confidence Interval from Bootstrapped Sample		
	Cohort	Time Non-Homogeneous	Time Non-Homogeneous
Whole Sample vs. Female	**(-0.0091, -0.0042)**	**(-0.0720, -0.0711)**	**(-0.1066, -0.1053)**
Whole Sample vs. Male	(-0.0023, 0.0032)	(-0.0001, 0.0005)	(-0.0001, 0.0005)
Female vs. Male	**(0.0046, 0.0097)**	**(0.0713, 0.0723)**	**(0.1055, 0.1068)**
Whole Sample vs. White	(-0.0045, 0.0011)	**(-0.0007, -0.0001)**	**(-0.0006, -0.0001)**
Whole Sample vs. Non-White	**(-0.0071, -0.0023)**	**(-0.0872, -0.0861)**	**(-0.1239, -0.1224)**
White vs. Non-White	**(-0.0056, -0.0005)**	**(-0.0868, -0.0857)**	**(-0.1236, -0.1221)**

Bold number indicates p-value < 0.05 (95% Confidence Interval)

Table 4.5. Summary Matrices for All Farmers under the Cohort Method and Markov Chain Methods, 2004-2013 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes			
	1	**2**	**3**	**4**
	Time Discrete Cohort Method			
1	45.48†	28.95	18.38	7.19
2	19.43	41.47	26.24	12.87
3	10.11	27.71	42.62	19.57
4	6.76	21.94	33.72	37.57
	Time-Homogeneous Markov Chain Method			
1	38.76	25.59	23.44	12.21
2	14.70	46.30	25.25	13.75
3	12.05	24.50	48.03	15.42
4	11.23	23.10	26.72	38.95
	Time Non-Homogeneous Markov Chain Method			
1	26.73	32.80	27.07	13.40
2	17.87	34.47	30.98	16.68
3	14.03	31.10	35.00	19.86
4	12.09	28.70	34.40	24.81

† The matrices are derived based on biannual transition, which means instead of using one-year horizon in any two-year period, we used a two-year horizon.

Table 4.6. Summary Matrices for Female Farmers Under the Cohort Method and Markov Chain Method, 2004-2013 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes			
	1	**2**	**3**	**4**
	Time Discrete Cohort Method			
1	41.96	29.47	19.46	9.11
2	16.18	36.61	30.36	16.85
3	6.75	22.60	46.75	23.90
4	5.47	16.42	34.44	43.67
	Time-Homogeneous Markov Chain Method			
1	32.41	24.18	27.08	16.33
2	11.15	43.65	28.06	17.14
3	8.32	20.75	51.92	19.02
4	8.25	19.08	28.44	44.23
	Time Non-Homogeneous Markov Chain Method			
1	21.94	30.30	30.10	17.66
2	15.17	31.03	33.67	20.13
3	11.44	27.12	37.59	23.85
4	10.11	24.50	36.10	29.29

Table 4.7. Summary Matrices for Male Farmers Under the Cohort Method and Markov Chain Method, 2004-2013 (percent)

Period 1 Farm Credit Risk Classes	**Period 2 Farm Credit Risk Classes**			
	1	**2**	**3**	**4**
	Time Discrete Cohort Method			
1	45.28	29.17	18.48	7.07
2	19.45	41.79	26.16	12.60
3	10.20	27.85	42.57	19.38
4	6.66	22.27	33.73	37.34
	Time-Homogeneous Markov Chain Method			
1	38.81	25.71	23.44	12.04
2	14.76	46.31	25.30	13.63
3	12.14	24.66	47.84	15.35
4	11.25	23.32	26.78	38.65
	Time Non-Homogeneous Markov Chain Method			
1	26.81	32.95	27.03	13.21
2	17.78	34.60	31.03	16.58
3	13.94	31.20	35.10	19.76
4	11.96	28.83	34.52	24.69

Table 4.8. Summary Matrices for White Farmers Under the Cohort Method and Markov Chain Method, 2004-2013 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes			
	1	**2**	**3**	**4**
	Time Discrete Cohort Method			
1	45.93	28.94	18.12	7.01
2	19.73	41.56	26.09	12.62
3	10.38	28.03	42.30	19.30
4	6.90	22.44	33.80	36.85
	Time-Homogeneous Markov Chain Method			
1	39.31	25.67	23.15	11.88
2	15.00	46.55	25.02	13.43
3	12.36	24.74	47.79	15.11
4	11.47	23.36	26.58	38.58
	Time Non-Homogeneous Markov Chain Method			
1	27.20	32.95	26.75	13.10
2	18.12	34.71	30.75	16.42
3	14.26	31.34	34.81	19.60
4	12.23	28.95	34.21	24.60

Table 4.9. Summary Matrices for Non-White Farmers[a] Under the Cohort Method and Markov Chain Method, 2004-2013 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes			
	1	**2**	**3**	**4**
	Time Discrete Cohort Method			
1	35.11	29.33	24.16	11.40
2	12.95	39.61	29.37	18.07
3	5.91	22.75	47.59	23.75
4	4.86	14.96	32.69	47.49
	Time-Homogeneous Markov Chain Method			
1	30.09	23.76	28.34	17.80
2	9.72	42.20	29.00	19.07
3	7.56	20.65	51.73	20.05
4	7.69	18.93	28.77	44.61
	Time Non-Homogeneous Markov Chain Method			
1	17.60	30.27	32.88	19.24
2	12.88	30.14	35.36	21.61
3	10.29	27.00	38.19	24.52
4	9.49	24.61	37.20	28.71

Table 4.10. Results of Random-Effects Logistic Regression, Year 2006-2012

Independent Variable				
Variable	**Description**	**Coefficient**	**Standard Error**	**Z Statistics**
Size	Log(total assets)	0.0625	0.0181	**3.45*** **
ATO	Asset turnover ratio	0.0190	0.0444	0.43
Age	Age at credit action date	0.0028	0.0010	**2.88** **
SP500	Percentage change in S&P 500 index	-0.0080	0.0023	**-3.47*** **
Money_M2	Percentage change in money supply (M2)	0.0271	0.0160	**1.70* **
Unemployment	Unemployment rate	-0.0027	0.0111	-0.24
Income_Change	State level income change	0.0219	0.0083	**2.64** **
Gr_livestock_production	Livestock growth rate	0.9870	0.2304	**4.28*** **
Population_density	Population density	0.0358	0.1405	0.25
Dependent Variable				
Y=0 for Downgrade				
Y=1 for Retention				
Y=2 for Upgrade				

*** Significant at 1%, ** significant at 5%, * significant at 10%

Table 4.11. Marginal Effects of Random-Effects Logistic Regression

Significant Variables	Downgrade	Retention	Upgrade
Size	-0.0118	-0.0009	0.0127
Age	-0.0005	-0.00004	0.0006
Sp500	0.0015	0.0001	-0.0016
Money_M2	-0.0051	-0.0004	0.0055
Income_Change	-0.0041	-0.0003	0.0044
GR_livestock_production	-0.1857	-0.0145	0.2002

CHAPTER 5

Summary and Conclusions

5.1 Summary and Conclusion

The primary goal of this dissertation is to evaluate and compare the performance of lenders and borrowers before, during, and after the late 2000s financial crises. From a lender's perspective, the financial crises of 2007-08 was a significant setback to the banking sectors. More than 500 banks failed from 2007 through 2013, and hundreds of banks were in the watch list maintained by FDIC by the end of 2014. Such unfortunate economic misfortunes, however, can provide useful insights and lessons that can help regulators to understand the causes of bank failure, and detect early warning signals that can be used to prevent banks from closure as early as possible. From a borrower's perspective, their financial performance needs to be carefully evaluated to draw enough attention to certain important indicators of borrower quality that FSA can pay attention to and motivate FSA to make corresponding policy changes.

The first paper focuses on applying the Input Distance Stochastic Frontier Function to estimate the technical efficiency (TE) and allocative efficiency (AE) between Agricultural Banks and Non-Agricultural Banks (Commercial Banks). Recent literature has discussed the effectiveness of early warning model to predict bank failure. Li et al (2013) contends that bank failures can be predicted as early as three to four years prior to the actual event through crucial operating decisions affecting funding arrangements, interest rate risk, and asset quality and adequacy, among others. This paper is designed to revisit and validate these contentions by scrutinizing certain components of operating decisions made by banks in a seven year period before the onset of banking crisis from the aspect of efficiency analysis. Both TE and AE measures are calculated and compared between those banks that eventually survived the economic crisis and those that became critically insolvent, and between commercial banks and agricultural banks.

In terms of technical efficiency, the results indicate that both agricultural banks and commercial banks were not technically efficient before the recession since the average efficiency level between these two types of banks are only 0.34. TE level of surviving agricultural banks are significantly different than efficiency level of critically insolvent non-agricultural banks. However, the efficiency level between agricultural banks and non-agricultural banks are not statistically significant different from each other. Although the predictive power from their comparative efficiency is weak, results show that banks' input allocation decisions reveal some interesting pattern that can be used to predict banks' performance few years in advance. Compared to non-agricultural banks, agricultural banks have shown greater inclination to prefer cheaper input such as financial capital rather than physical capital. On the other hand, agricultural banks' preference over relative expensive labor inputs is due to their limitations in collecting deposits and expanding physical locations. With strong agricultural product price and land values, it is not surprising to see the more regulated agricultural banks eventually weathered the recession.

The second paper is designed to apply a more advanced split-population duration model in analyzing the role of agricultural loan portfolios on the probability of survival and temporal endurance of commercial bank lenders in the late 2000s recession. The use of duration model to explain and predict bank failure is a relatively more recent approach compared to Discriminant Analysis such as logistic model. However, the duration model can provide more information than logistic regression because of its capability to generate not just estimates of the probability of bank failure but also estimates of probable time to failure. Moreover, the Split-population duration model used in this paper even has advantages over regular duration model (e.g. Cox proportional hazard model) such that: First, it does not assume that every bank would eventually fail as risk is magnified through time, which is not a valid assumption in banking industry; second, the likelihood function developed by split-population model can distinguish between the determinants of failure and the factors influencing the timing of failure, which cannot be revealed in a basic duration model design.

Results indicate that when compared to the determinants that can explain the probability of bank failure, only a part of them are helpful in explaining the duration time. This analysis therefore presents some interesting insights on the exaggeration of certain variable effects in basic duration models that can be rectified with the proper assumption of heterogeneity of bank failure experiences inherent in the split-population model. Delinquency measurements related to agricultural portfolios are not significant in predicting either the probability of survival or the length of survival. On the other hand, results indicate that bank failures could have resulted from changes in the quality of the banks' portfolios of real estate, consumer, and industrial loans as well as factors capturing interest rate risk and some fund sourcing strategies.

The third paper explicitly analyzes the qualities of farm loan borrowers within the Farm Service Agency (FSA)'s direct loan lending program. FSA is considered as a lender of last resort since it is designed to fill the gaps in the commercial credit market in which creditworthy farmers, especially high-risk borrowers, are unable to obtain credit. Those farmers who have been facing credit issues are mostly beginning farmers that have insufficient financial resource and established farmers who may have experienced financial hardship. Moreover, FSA is expected to ensure that socially disadvantaged borrowers belonging to racial and gender minority groups are given fair access to credit needed to sustain their farm business operations. This loan program has played an even more important role during economic downturn. FSA farm loans have been substantially increased from 2008 to 2010 to support farmers who are facing unique credit and debt burdens and those farmers who have faced downturn in prices in several farm sectors and those in the Midwest who have faced severe drought disaster in 2012.

This study has utilized two time continuous Markov Chain models in lieu of the traditional cohort model. Results indicate that Markov Chain time continuous model are able to capture the intermediate transition rates that are omitted from the cohort method. Different migration matrices are compared using Singular Value Decomposition (SVD), and significant difference were detected among three different methods. These results suggest that the industrial standard “cohort” method could result in more costly omission of transient changes in credit risk rating, and in turn, produce misleading indicators of farm loan portfolio quality such as loan default probability estimates. On the other hand, Markov models could provide more accurate, reliable representation of farm credit risk migration activities.

The results from credit migration indicate that racial and gender minority farms experienced more credit downgrade in the past ten years when compared to male white farmers. In addition, ordered logistic regression is used in this study to further evaluate the impact of farm level structural and demographic variables, as well as macroeconomic indicators. The results suggest that economies of scales (farm size) played an important role in increasing the probability of upgrade, while some macroeconomic variables such as money supply and income growth have positive impact on the credit migrations.

5.2 Recommendation for future research

This study applied different methodologies to evaluate performances from both lenders and borrowers during the economic hardship. There are several possible avenues for future improvements.

Technical efficiency and allocative efficiency are examined on either agricultural banks or non-agricultural banks before the recession in order to discover any pre-recession signals that can be used as predictor of banks' performance during the recession. However, a more complete picture would be given if the efficiency estimation is also applied on the time period from 2008 to 2015, which covers the recession period when most of the banks failed and post-recession time when bank recovery can be carefully tracked. Future studies would involve the comparison of both technical efficiency and allocative efficiency between different types of banks in different time periods.

Split-population duration model can estimate the likelihood of bank failure and timing of bank failure at the same time. However, one shortcoming of the analytical model is it only studies the impact of independent variables at one time point. Unlike Cox proportional hazard model, split-population model does not allow time-varying covariates and therefore restricts its ability to utilizing any panel level data that can track the variable change over time. It would be more illuminating to develop a model that allows time-varying covariates and also distinguishes those factors that affecting the probability of survival from those affecting the timing of survival.

The credit migration study has revealed some interesting features about racial and gender minority farmers, as well as young and beginning farms. Those types of farms have shown less probability of upgrade in the study period when comparing with white male farmers. However, since the major participants of this FSA lending program are male white farmers, we cannot draw the conclusion that female farmers are doing worse than their male counterpart. In addition, it would be more interesting to compare female and male farmers, non-white and white farmers after controlling for any geographic or size effects. It would be interesting to select different types of farm from a similar geographic location or under the same size, and then compare their credit migration probabilities. In order to achieve this, a loan accounting data with larger observations from USDA would be needed to obtain enough sample from different segmentations.

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