BUSINESS SURVIVAL STRATEGIES OF FARMERS AND LENDERS UNDER FINANCIAL AND NATURAL ADVERSITIES: ANALYSIS OF TECHNOLOGICAL ADOPTION ISSUES, INPUT ALLOCATION DECISIONS, AND REGIONAL DIFFERENCES IN FINANCIAL ENDURANCE

by

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(Under the Direction of Cesar Escalante)

ABSTRACT

This dissertation consists of three studies and focuses on the coping mechanisms of agricultural producers and lenders as they responding to natural and economic adversities. The studies address several important issues ranging from technology adoption of hybrid seeds in South African countries to how lender and borrower perform in financial and natural hardship.

The first study focuses on the smallholders' technology adoption of hybrid seeds in response to drought conditions. The hybrid seeds adoption patterns of smallholder farmers in Kenya from 1990's to early 2000's are analyzed. This can help government in the developing countries to implement effective policies to increase both percentage of adoption of hybrid seeds and the quantities of adoption. Credit restriction and difficulty of access to market and infrastructure are major barriers for smallholder farmers to adopt new technology.

The second study applies the stochastic Translog input distance function and stochastic frontier analysis (SFA) method to evaluate the operational efficiencies of Farm Credit System (FCS) lending institutions. According to the FCS structure, the efficiency analysis is conducted on lending institutions classified based on type (such as banks and associations) and on asset size. Moreover, we compare the temporal efficiencies of FCS lending institutions before and after the most recent financial crisis. In addition, the study addresses the measurement of technical efficiency change (TEC) and allocative efficiency change (AEC). This will help clarify the contributions of different factors to total factor productivity change and, thus help FCS make operating adjustments to maximize total factor productivity.

The third study employs comparative analytical techniques that evaluate farmers' financial and temporal endurance during the recession period. We analyze the loan performance of farm borrowers in the loan program of the Farm Service Agency (FSA). FSA provides supports to farmers with lower credit scores with direct and guarantee loan programs. The split population model is employed to analyze the determinants of both the probability of loan default and the length of time until the eventual occurrence of default.

INDEX WORDS: technology adoption, box-cox double hurdle model, stochastic frontier analysis, technical efficiency, allocative efficiency, split population model

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DEDICATION

This dissertation is dedicated to the most important people in my life. To my mother, Jianfeng Fan, and to my father, Yaoji Song, for giving me all the loves and supports. To my wife, Shiming Dong and to my son, Kevin Song, for being a great family.

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CHAPTER 1

INTRODUCTION

1.1 Background

Disasters caused by natural hazards pose great threats to all human beings as damages caused by these adversities can come in many forms affecting lives, economies, and societies. A great proportion of the world's population most vulnerable to the threats of violent events, illness, and hunger are in less developed countries (Wisner et al., 2003). According to the data from the Centre for Research on the Epidemiology of Disasters (CRED), the natural hazard type that contributes most to death from 1900 to 1990 is famine. Famine is usually brought about by drought conditions and is exacerbated by a rapidly increasing world population. The current worldwide population has been projected to increase from 7 billion to 9 billion by 2050 (Lutz et al., 2010). This growth will require food production to increase significantly from 6 billion tons to 9 billion tons by 2050 (Borlaug and Carter, 2005). According to projections developed by the U.S. Department of Agriculture, developing countries will account for more than 80% of the anticipated growth of global consumption of meats and crops from 2013 to 2022 (Trostle and Seeley, 2013). However, food security is still a problem in less developed countries in Africa. Food security and famine have been phenomena that occurred repeatedly in South Africa in the twentieth century (Ansell et al., 2009). For example, there was a food crisis in South Africa in the spring of 2002. More than 14 million people were in the danger of experiencing famine and an estimate of 1 million metric tons of food was required to meet emerging demand (Zerbe, 2004).

Looking at food production trends, the world's 450 million smallholder farmers (UNDESA 2007) are mostly located in Africa, Asia, and Latin America. They are an increasingly important sector of the global food market. However, many smallholder farmers still live in poverty. Many smallholder farmers in Africa depend on maize as a subsistence and cash crop. They often use simple and outdated technologies with low returns and high risks, but they are still a driving force in the economies of many African countries. On one hand, people have weaknesses and limitations and tend to adopt a passive stance to change. A majority of smallholder farmers in South Africa plant less than one acre of maize and the size of the maize crop planted depends on the success of the previous season and potential rainfall at planting season (Gouse et al., 2009). On the other hand, people have capabilities to create security and improve social and economic status. With the introduction of hybrid seeds, smallholders can increase crops' yield and drought resistance and reduce their diseases and risks. It is important to understand smallholders' hybrid seeds adoption patterns and what factors contribute to improving the adoption process. This can help governments implement more effective policies to improve smallholders' adoption of hybrid seeds.

Many smallholders have pointed out that the lack of financial capital is a major reason for their decisions not to adopt new beneficial technologies. The opportunity for smallholders to increase their income depends on their ability to compete in the market, but it could be restricted by access to and availability of financial capital and technology expertise (Markelova et al., 2008). Research has also suggested that farmers with less access to credit plant few high yielding crop varieties. Smallholders need funds to buy hybrid seeds and fertilizer and lease equipment to prepare for land. Limited access to financial products and services is a significant barrier for smallholder farmers, because either financial services are not available or smaller farmers with low credit ratings often do not fare well in the applications for funds from potential lenders. An estimated smallholder demand for financing suggests the market could be as large as $450 billion with the vast majority of the needs unmet.

The experience of financial adversity, however, is not limited solely to the producer's perspective. Even the suppliers of financial capital also have to deal with almost the same financing predicament as smallholders experience, except that their financial concerns or woes are much larger in scale. In this regard, it would be interesting to not only analyze the financial predicament of smallholders struggling through financial adversary, but it would also be important to examine the operational efficiency of farmer lenders as it can be affected by the volatility of economic conditions. Whether farmer lenders do a good job to serve smaller farmers is highly related to the success of these famers' business operations.

A case in point that will be explored in this study is the Farm Credit System (FCS), which is a government sponsored enterprise in the United States. FCS provides credit and financial services to farmers, ranchers, producers or harvesters of aquatic products, and agricultural and aquatic cooperatives. In 2013, FCS has more than $260 billion assets and nearly 500,000 member borrowers, including many smallholder farmers. FCS provides more than $191 billion in loans, which consist of more than one third of the credit needed by American people living and working in rural areas. Overall, commercial banks and the FCS hold 84% of total agricultural debt (Ellinger, 2011). As a major source of financial capital for farmers, FCS's operational efficiencies and financial health are very important to the success of smallholder farmers.

Farm borrowers with unfortunate borrowing experiences with regular lenders, like commercial banks and the FCS lending units, are given some recourse under the U.S. farm finance system. When farm borrowers are unsuccessful in their loan applications with regular lenders because of stringent requirements, such as business experience, loan collateralization, minority status of primary borrower, or the relative size of the business vis-à-vis the lenders' usual pool of farm loan clients, the government has a farm lending arm that comes to the rescue of such farm borrowers. These borrowers may find help from the Farm Service Agency (FSA), which is an agency of the U.S. Department of Agriculture (USDA) and is guided by federal government to provide credit to farmers. FSA's mission is to provide loans to less creditworthy farmers, who may experience difficulty to gain access to funds through the commercial credit market. FSA has been regarded as the farmers' "lender of last resort", because borrowers need to prove that they had been denied loan requests by commercial lenders (Escalante et al., 2006). FSA has two loan programs, the direct loan program and the guarantee loan program, representing two steps to help borrowers to reach financial independence. The direct loan program provides direct loans to borrowers with farm ownership, operating, emergency and youth loans as main types of loans. Under the FSA guaranteed loan program, farmers borrow from commercial lenders and FSA guarantees loans providing lenders with a guarantee of up to 95% of loss of principle and interests to a loan. The FSA guarantee loan program helps commercial lenders provide credit to borrowers, who are not qualified under normal commercial loan approval criteria. FSA intends to guide direct loan borrowers towards guaranteed loan programs and graduate guaranteed loan borrowers towards regular commercial credit.

However, there can be periods when economic stability is threatened by external shocks. The financial crisis of 2007-2008 is considered by many economists to be the worst financial crisis since the Great Depression of the 1930s. The crisis caused failures of key businesses, declines in consumer wealth estimated in trillions of dollars, and downturn in global economic activities leading to the 2008-2009 recession. The global recession raised the risk environment for both FCS and FSA loan programs. According to a study from the Federal Reserve Bank of Kansas City, farm capital spending and operation loans actually peaked in late 2007. However, FCS found it difficult to raise capital and at the same time asset valuations were declining during the recession. To better serve farm borrowers, FCS needed to maintain capital ratios and meet certain liabilities.

Some farmers in the United States found a hard time to sustain their business during the 2007-2009 financial crises. The credit market was so tightened up that farmers with low credit ratings found it difficult to secure a loan to keep their business running. To make things even worse, there were several severe droughts through the 2000's that hit some areas in Midwestern and Southeastern states hard.

The Farm Service Agency (FSA) from United States Department of Agriculture implemented the direct loans and guaranteed loan programs. Both programs will help farmers with low credit rating, whose loan applications might been rejected by commercial financial institutions.

1.2 Major Study Goals and Objectives

In essence, all major players in the food production industry can possibly be exposed to some form of crises that can basically be primarily classified as natural and economic shocks. A natural climatic or weather disturbance in the amount of rainfall or levels of temperature, for instance, can bring about drought conditions that may affect certain food production regions at different intensities. Smaller farms stand to be more vulnerable to these external shocks from nature. The production sector stands to be directly affected adversely by such phenomenon, while the institutional agents surrounding these farm businesses, such as their lenders, are also eventually affected.

In addition, imprudent business decisions, especially of influential players in the economy, and the volatility they bring to important economic parameters can usher in a period of financial panic and crises, such as the recession of the late 2000s. Such economic downturns do not only affect directly the producers but practically the entire economy, including the large institutional lenders.

This study's general theme centers on the coping mechanisms of producers and lenders as they respond to natural and economic adversities. These adversities will initially be analyzed separately in the first two studies: the first study focuses on the smallholders' technological response to drought while the second looks into the input allocation strategies of a major farm lending institution in overcoming the effects of the last recession. A third study will look at both these two types of adversities from the producers' perspective.

Specifically, using household survey data from Kenya, the first article studies maize hybrid seeds adoption patterns of the smallholder farmers in South Africa from middle 1990's to early 2000's. This can help government in the developing countries to implement effective policies to increase both adoption of hybrid seeds and the quantities of adoption. Credit restriction is one of the major barriers for smallholder farmers to adopt new technology.

Moreover, this research will also analyze two perspectives of the farm economy, the farm lenders and borrowers. On one hand, the effectiveness of the input allocation strategies during the last recession of one of the major farm credit providers, the Farm Credit System, will be analyzed. On the other hand, farmer borrowers' risks and financial performance will be studied from the farm loan clients of Farm Service Agency loan programs. Both farm lenders and borrowers' performance will be evaluated and compared during the pre-recession and post-recession years. The following sub-sections will provide more details on the objectives and approaches of the three studies in this dissertation.

1.2.1 New Technology Adoption Decision by Smallholder Farmers

Smallholder farmers in Southern Africa depend on maize as subsistence and a major cash source. Hybrid seeds increase annual yields and drought and disease resistance, although they need to be purchased by farmers every year. Several big seed companies developed commercial hybrid seeds and made them available globally. We study production decisions made by smallholder farmers in Kenya with regards to hybrid seeds. Several factors including weather, production conditions, demographic characteristics, financial restrictions, public infrastructures, and other technologies used are examined. Using econometric models, we try to indentify key factors which drive the decision process of smallholder farmers. In addition, we examine the factors that impact the quantities of the hybrid seeds that smallholder farmers use.

1.2.2 Input Allocation Decisions of Farm Credit System Lending Units

We apply the stochastic Translog input distance function and stochastic frontier analysis (SFA) method to evaluate the operational efficiencies of Farm Credit System (FCS) lending institutions. According to the FCS structure, the efficiency analysis is conducted on lending institutions classified based on type (such as banks and associations) and on assets size. Moreover, we compare the temporal efficiencies of FCS lending institutions before and after the most recent financial crisis. In addition, the study addresses the measurement of technical efficiency change (TEC) and allocative efficiency change (AEC). This will help clarify the contributions of different factors to total factor productivity change and, thus help FCS make operating adjustments to maximize total factor productivity. This analysis may also clarify any differences in input allocations and other operating decisions that define small and large lenders' strategies to survive the tight financial conditions of the late 2000s.

1.2.3 Farmers to Maintain Business Viability through the Financial and Natural Adversities

U.S. farm businesses experienced difficulty in obtaining much needed loans during the 2007-2008 financial crises. Many commercial lenders tightened their borrowing criteria during the recession. To make things worse for farmers, there had been several droughts that hit certain regions in the country. Moreover, there was a significant drop in the food and beverage commodity prices in 2008 and 2009. The financial and natural adversities during the late 2000s altogether created dire, challenging operating environments for farm businesses that struggled to maintain business viability.

This study will employ comparative analytical techniques that evaluate farmers' financial and temporal endurance during the recessionary period. The analyses will be interested in looking at differing strategies and endurance based on geographical locations, farming activities, and size of operations. Specifically, the geographical focus will be on Southeastern and Midwestern regions to discern whether the inherent structural differences in business environments and profiles in these regions will define or influence farmers' survival strategies. We also focus on analyzing the loan performance of farm borrowers in the loan programs of the Farm Service Agency (FSA). FSA provides supports to farmers with lower credit scores with their direct or guarantee loan programs. We use standard survival models to compare the cumulative hazard functions of different regions or construct the Kaplan-Meier survival curves. For this purpose, the split population model is employed to analyze the determinants of both the probability of loan default and the length of time until the eventual occurrence of default.

1.3 Organization

This dissertation has five chapters. Chapter 1 gives introduction and overview of the entire scope and general theme of this dissertation. Chapter 2 examines the decisions of new technology adoption through time with evidence from Kenya. Chapter 3 presents the stochastic frontier analysis of efficiencies and input allocation decisions of Farm Credit System during the pre and post recession periods. Chapter 4 presents the split population duration analysis that evaluates the loan performance of FSA borrowers from different USDA regions. Chapter 5 concludes the results of all three studies and discusses potential future work.

CHAPTER 2

Examining the Decisions of New Technology Adopters through Time: Evidence from Kenya

2.1 Introduction

Maize has been one of the most important agricultural crops for centuries (FAO 2009). More than 1.2 billion people in sub-Saharan Africa and Latin America rely on maize as a staple food. In developing countries, especially those in Africa, many smallholder farmers depend on maize as a subsistence and cash crop. In Kenya, maize is estimated to contribute to 20% of total agricultural production and 25% of agricultural employment (Muasya, 2001). The introduction of hybrid crop varieties is one of the most significant technology breakthroughs in less developed countries' agricultural sectors (Schroeder, 2013). Local seeds can be improved by purposely selecting the better ones, but pollination is very hard to control. Hybrid seeds are created by the cross-pollinating process, in which crosses are specified and controlled. The benefits of growing hybrid seeds as opposed to normal seeds in agriculture come from the out-breeding enhancement, which improves biological quality as a result of mixing genetic contributions of the parents. Hybrid seeds are produced to increase yield and drought resistance, and reduce diseases and risks.

The Green Revolution in the 1960's and 1970's depended on irrigation, hybrid seeds, and chemical fertilizers and pesticides (Hazell, 2009). Under this program, India increased its wheat production tenfold and its rice production threefold (Pingali, 2012).

New varieties of wheat, rice and maize spread quickly through Asia to replace local varieties. The adoption of hybrid seeds in Africa has not been as smooth as in Asia. Smallholder farmers in sub-Saharan Africa must deal with difficult environmental factors, such as harsh weather and less productive land. They may also be restricted by limited cash or credit, hampering their ability to buy hybrid seeds and fertilizers every year. Poor infrastructures also limit information dissemination regarding the adoption of hybrid seeds.

In this paper, we focus on sequential production decisions with regards to hybrid seeds made by small-scale agricultural producers in Kenya. We examine the behavior of farmers with respect to adoption, seed intensity and acreage over time. There is much literature that developed either theoretical or empirical models for the behavior of first adopters of the new technology (e.g. Yoav and Shchori-Bachrach, 1973; Hiebert, 1974; Feder and O'Mara, 1981; Isham, 2002; Cavane and Donovan, 2011). Suri (2011) showed how the unobserved heterogeneity in the yield function is a key determinant in the profit comparison to drive the hybrid decision. We examine the successive behavior of adopters to gain a better understanding on whether they increase adoption, reduce adoption, or even drop the new technology and return to local seeds. This is important for several reasons. First, a better understanding of adoption behavior can lead to increased efficiency in increasing adoption and productivity. Second, we need to know the determinants of dis-adoption in order to improve the technology. Third, learning whether first adopters increase their planted areas from year to year can shed light on farmers' cropping strategies and help identify longer term successful technology that increase their income. We also employ several models to gain a better understanding of the adoption decisions of smallholders over time and to understand what attributes contribute to smallholder's changes of the quantity of hybrid usage.

For the purpose of this study, we use survey data collected in 1997, 1998, and 2000 by Egerton University. A panel data set of four periods (1996, 1997, 1998, and 2000) containing samples of four hundred and forty-one households across different regions of Kenya is used.

The paper is organized as follows. Section 2 reviews the literatures on theoretical and empirical models on adoption of new agricultural technology, including hybrid seeds. Section 3 contains information of the survey data and models used. Section 4 describes model estimation results and suggests policy implications. Section 5 provides conclusions.

2.2 Literature Review

Several authors have developed theoretical or empirical models of farmers' decisions to adopt new technology (Yoav and Shchori-Bachrach, 1973; Hiebert, 1974). Based on the assumption that an innovation is first adopted by more skilled people, Yoav and Shchori-Bachrach (1973) developed an "innovation cycle" model that includes a learning-by-doing knowledge component (Arrow, 1962) in the production function. They assumed that innovation will be "first adopted by skilled and experimenting entrepreneurs and then diffuses down the skills scale." The adoption process is affected by both the distribution and level of skills. They applied the model to the diffusion of a new technology of growing winter vegetables under plastic cover in Israel. The results were in line with what the model predicted; High skilled and educated farmers adopted first and then the technology was diffused to other less skilled farmers. Hiebert (1974) examined the effect of uncertainty due to imperfect information on the decision to adopt seed varieties that are responsive to fertilizers. Learning by gathering additional information about the unknown parameters will reduce the possibility of allocation errors and increase the chance of adoption (Hiebert, 1974).

Several other studies have modeled new technology adoption as a Bayesian learning process, in which each period's experience is used to update beliefs about the new technology in the next period (Lindner, Fischer, and Pardey, 1979). A theoretic model of decision making was developed to deduce the time from a decision maker's first knowledge of the new technology to his or her first adoption. Only limited information is gathered in each period. Based on the previous accumulated knowledge, a decision is made at the end of the period about whether to adopt the new technology or not in the next period. If the innovation is profitable, the favorable experiences accumulated will cause more farmers to adopt the new technology.

Feder and O'Mara (1981) assumed that there are fixed adoption costs, which are not a characteristic of the new technology, but are "a result of information acquisition requirements, inefficient input distribution system, and credit facility burden". The model and the simulation results showed the differential adoption pattern among farmers, and learning and information diffusion is a factor to reduce uncertainty and induce risk-averse farmers to adopt. Instead of treating information accumulation as a passive process, Feder and Slade (1984) developed a dynamic decision model of new technology diffusion based on improved knowledge through active information accumulation, which is not free. Such costs are not a characteristic of the new technology, but are incurred by the information acquisition process. Their model predicts that farmers with more education and more lands will have more knowledge of the new technology and will adopt more quickly.

To incorporate social capital as an input, Isham (2002) extended the Feder and Slade model and tested how social structure affects adoption decision of a new technology. Isham (2002) formally introduced human capital into the model and assumed that "the quantity of public information is affected by the village-wide cumulative proportion of adopters and village-wide social capital". Their model predicts that farmers with neighbors who have adopted the new technology and with higher levels of social capital will adopt technology more quickly.

Cavane and Donovan (2011) studied the adoption of improved maize seed and chemical fertilizers in Mozambique. They found that farmers' decision to adopt new hybrid seeds was positively associated with favorable agro-ecological conditions, knowledge, production traits and marketability of the maize. The decision to adopt a chemical fertilizer depends on agro-ecological conditions, knowledge of fertilizer application, and extension services. Their results showed that a simpler process of adoption of new seed is different from a more complex process of adoption of fertilizers which demands greater knowledge of timing and soils as well as basic computational skills. They suggested that factors determining adoption of hybrid maize varieties and chemical fertilizers should be considered when designing extension programs for these technologies.

Suri (2011) considered a model and empirical approach that allows for heterogeneous returns to hybrid seeds that correlated with the hybrid adoption decision.

2.3 Methodology

Theoretical model

We build a theoretical model based on Lindner, Fischer, and Pardey's (1979) decision maker model. Suppose there a decision maker *i*, who at time *t* = 0 learns of a new technology, *A*. *A* is a potential alternative to the current best practice technology *B*. For simplicity, we assume that the extra profits for smallholder *i* in year *t* from adopting new technology *A* are solely a multiplication of a function of individual specific variables, Q_i, and an unknown state function C_{it}.

$$Q_i = f(\vec{x}) \tag{1}$$

$\vec{x}$ is a vector of individual specific variables, such as age, gender, education, land size etc. C_{it} is an unknown state variable and its actual value in any given year will depend on high-order state variables, like weather conditions. C_{it} can not be predicted by the decision maker *i*, when he or she must decide to choose option *A* or *B*.

The difference of profits between adopting new technology *A* and staying with old technology *B* is:

$$\Pi_{it}(A) - \Pi_{it}(B) = Q_i * C_{it} \tag{2}$$

where $\Pi_{it}(A)$ is the profit of adopting new technology *A* by smallholder *i* in year *t*.

We assume that the state variable C_{it} is normally and independently distributed through time with mean μ_i and variance σ_i^2. As the model is specific to a given smallholder, the *i* subscript can be dropped so that for any given *t*, C_t is distributed as *N* (μ, σ^2). The breakeven value of μ is zero, so the decision maker will adopt *A* if $\mu > 0$, and stay with *B* if $\mu \leq 0$.

Empirical Approach

Logistic model

As mentioned in the introduction, this paper assesses the production decision on hybrid seeds by smallholders in Kenya. In addition, we want to model the behavior of initial adopters after first adoption. In this study, we use a four year panel data survey of 441 randomly selected householders who grew maize in various agro-ecological zones in Kenya.

A logistic model is commonly used to describe farmer's decision to adopt the new technology or not. Cavane and Donovan (2011) used a cross-section logistic model to model whether small farmers in Mozambique adopted improved maize seeds and chemical fertilizers. We model adoption of new technology using the logit model with a binary response variable (1= adoption of new technology and 0 = no adoption), but enrich the model with a panel data setting. We would like to find out what factors increase the probability to adopt new technology and what factors will actually reduce the probability to adopt.

The random effects panel logistic regression model characterizing the adoption of hybrid maize seeds is specified as follows:

$$p(y_{i,t}|x_{i,t},\beta,\alpha_i) = \Lambda(\alpha_i + x'_{i,t}\beta) \quad (3)$$

where:

p is the probability that farmers adopt the new hybrid seeds conditional upon independent variables $x_{i,t}$ and $\alpha_i$that influence adoption. The β are the regression coefficients associated with independent variables $x_{i,t}$and α_i is constant.

Ordered logit model

To our knowledge, there are no studies that examine the determinants of adoption retention or dis-adoption and planted area changes related to repeated adoption. After initial adoption, the adopters have the choice to increase the scales of adoption, keep the same level of adoption, reduce the scale of adoption, or even dis-adopt. We use an ordered logit model to examine such behaviors for adopters. The ordered response variable $y=0$ if the adopter dropped the new technology, $y=1$ if reduced scale, $y=2$ if kept the same scale, and $y=3$ if increased scale.

Tobit Model

We also want to quantify the amount of hybrid seeds smallholder uses annually. This will help us understand what attributes will contribute to smallholder's increase or decrease the quantity of hybrid seeds. Tobit model is typically used to model censored data.

Define the latent variable:

$$y^* = x\beta + \varepsilon, \ \ \varepsilon \sim N(0, \sigma^2) \tag{4}$$

We observe y, which is the quantity of hybrid seeds a smallholder uses in a given year:

$$y = \begin{cases} y^* & if\ y^* > 0 \\ 0 & if\ y^* \leq 0 \end{cases} \tag{5}$$

The conditional mean of y is

$$E[y|y > 0] = x\beta + \sigma \left[\frac{\phi(x\beta/\sigma)}{\Phi(x\beta/\sigma)}\right] \tag{6}$$

The unconditional mean of y is

$$E[y] = \Phi(x\beta/\sigma)x\beta + \sigma\, \phi(x\beta/\sigma) \tag{7}$$

If x_j is a continuous variable, the conditional marginal effect of x_j is:

$$\frac{\partial E(y|x)}{\partial x_j} = \Phi\left(\frac{x\beta}{\sigma}\right)\beta_j \qquad (8)$$

The marginal effect helps us understand the magnitude of increasing or decreasing the quantities of hybrid seeds when smallholder has one more unit of x_j.

With regard to the level of $p(y > 0|x)$, which is the probability to adopt hybrid seeds,

$$\frac{\partial p(y>0|x)}{\partial x_j} = \phi(\frac{x\beta}{\sigma})\beta_j/\sigma \qquad (9)$$

Assuming β_j>0, both marginal effect and the level of $p(y > 0|x)$ increases as x_j increases. The Tobit model may not fit situations where a coefficient's marginal effect and marginal probability of $y > 0$ have different signs. It is possible that one explanatory variable may contribute positively to the probability of adoption and contribute negatively to the quantities of adopted hybrid seeds.

Double Hurdle Model

The Double Hurdle model (Cragg, 1971) is a two-tier model and is more flexible than the Tobit model. We can consider the Tobit model as a nested or restricted model of the Double Hurdle model. The Double Hurdle model contains two equations, one determines whether or not a smallholder is a potential adopter, and the other determines the extent of adoption. The model does not assume that a smallholder makes decisions in that sequence. Also, there is a probability that some smallholders will never adopt. It is meaningful to investigate whether a smallholder belongs to that non-adoption class based on his or her characteristics. Such considerations lead us to a class of models in which the event of a smallholder becoming a potential adopter, and the extent of adoption, are handled separately. This type of model is known as the 'Double Hurdle' and has been applied to a rich variety of contexts, such as individual consumption of cigarettes (Jones 1989), credit scoring literature (Dionne et al., 1996). The smallholders must pass two hurdles in order to adopt hybrid seeds. Smallholder must pass the "first hurdle" to be considered as a potential adopter. Conditioned on whether a smallholder is a potential adopter, he or she needs to pass the "second hurdle" based on current circumstances to decide whether to actually adopt or not. The Double Hurdle model has two equations:

$$d_i^* = z_i' \alpha + \varepsilon_i$$

$$y_i^{**} = x_i' \beta + \mu_i \tag{10}$$

$$\binom{\varepsilon_i}{\mu_i} \sim \text{BVN}\left[\binom{0}{0}, \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2 \end{pmatrix}\right]$$

The error terms of the two equations are assumed to be independent.

The first hurdle for a smallholder to be a potential adopter is:

$$d_i = 1 \; if \; d_i^* > 0$$

$$d_i = 0 \; if \; d_i^* \leq 0 \tag{11}$$

We observe whether a smallholder is an adopter when $d_i = 1$.

The probability for a smallholder to be a potential adopter is:

$$\omega = \Phi(z_i' \alpha) \tag{12}$$

where $\Phi(.)$ is normal distribution function.

The second hurdle is similar to the Tobit model:

$$y_i^* = \begin{cases} y_i^{**} & if \; y_i^{**} > 0 \\ 0 & if \; y_i^{**} \leq 0 \end{cases} \tag{13}$$

Finally, we observe the quantities of adopted hybrid seeds, y_i:

$$y_i = d_i y_i^* \tag{14}$$

The conditional mean of y is:

$$E[y|y > 0] = (z_i' \alpha) * \Phi\left(\frac{z_i' \alpha}{\sigma}\right) + \sigma \phi \left(\frac{z_i' \alpha}{\sigma}\right) \tag{15}$$

The unconditional mean of y is:

$$E[y] = (1-\omega) * ((z_i'\alpha) * \Phi\left(\frac{z_i'\alpha}{\sigma}\right) + \sigma\phi\left(\frac{z_i'\alpha}{\sigma}\right)) \quad (16)$$

Box-Cox Double Hurdle Model

The dependent variable, the quantities of hybrid seeds smallholders adopted, is positively skewed. The standard Double Hurdle model assumes bivariate normally distribution of unobserved errors (Equation 10). The maximum likelihood (ML) estimator of this model will be inconsistent when the normal distribution assumption is invalid. We may consider applying the logarithmic transformation to the dependent variable. However, there are lots of zeros (from non-adopters) in the dependent variable; we can not apply the logarithmic transformation.

Jones and Yen (2002) analyzed the generalized double hurdle model by introducing a Box-Cox transformation in the dependent variable and allowing dependence between the error terms of two hurdles. With the Box-Cox transformation, the normally distribution of unobserved errors assumption is valid. Smith (2002) questioned the relevance of the dependent double hurdle model and argued that the correlation parameter could be poorly identified. He suggested that independent double hurdle model is an acceptable alternative to the dependent model. This approach was adopted by Aristei and Pieroni (2007) to model tobacco consumptions in Italy.

The latent variables are similar to equation (10). The Box-Cox transformation on the observed dependent variable y_i can be explained as:

$$y^T = \frac{y^\lambda - 1}{\lambda}, 0 < \lambda \leq 1 \quad (17)$$

There are two specific cases. If $\lambda = 1$, it is a linear transformation. If $\lambda \rightarrow 0$, it is the logarithmic transformation. Generally, λ will fall between 0 and 1.

The first hurdle is:

$$d_i = 1 \; if \; d_i^* > 0$$

$$d_i = 0 \; if \; d_i^* \leq 0 \tag{18}$$

The second hurdle is:

$$y_i^{*^T} = \max\left(y_i^{**^T}, -\frac{1}{\lambda}\right) \tag{19}$$

Finally, we observe y^T:

$$y_i^T = y_i^{*^T} if \; d_i = 1$$

$$y_i^T = -\frac{1}{\lambda} if \; d_i = 0 \tag{20}$$

The likelihood function for the Box-Cox double hurdle model is:

$$L = \prod_{i=1}^{n} \left[1 - \Phi(z_i'\alpha)\Phi(\frac{x_i'\beta + 1/\lambda}{\sigma})\right]^{1-d_i} \times \left\{\Phi(z_i'\alpha) y_i^{\lambda-1} \frac{1}{\sigma} \phi(\frac{y_i^T - x_i'\beta}{\sigma})\right\}^{d_i} \tag{21}$$

Where $\phi(.)$ and $\Phi(.)$ are the univariate standard normal density and distribution functions, respectively.

2.4 Data and Descriptive Statistics

This study uses the Kenya rural household survey data collected by the Tegemeo Institute of Agricultural Policy and Development at Egerton University and the Kenya Central Bureau of Statistics in 1996, 1997, 1998, and 2000. The Tegemeo Institute developed the sample frame work with the Kenya Central Bureau of Statistics and randomly selected a number of households proportional to the population of each agro-ecological zone (AEZ). The survey contains information about household demographics, production characteristics, income, assets, cost factors, marketing activities, and government infrastructures (Argwings-Kodhek, 1997). A balanced panel was built based on the data for the years 1996, 1997, 1998, and 2000. As mentioned, we focus on the adoption of maize hybrid seeds and have a total of four hundred and forty-one households in four time periods.

Since weather may be an important driver for smallholder's decision making, we also collect annual rainfall data from the U.S. Agency for International Development (USAID) Famine Early Warning Systems Network (FEWS NET). The U.S. Agency for International Development (USAID) Famine Early Warning Systems Network (FEWS NET) is an information system designed to identify problems in the food supply system that potentially lead to famine or other food-insecure conditions in sub-Saharan Africa, Afghanistan, Central America, and Haiti. The rainfall data are distinguished at the village level. The annual rainfall amount per year in each agro-ecological zone is showed in table 2.1. Some agro-ecological zones had significantly more rain than other zones.

Summary statistics are reported in table 2.2. One of the dependent variables is adoption, which indicates whether a household adopted hybrid seeds in a given year. The other dependent variable is choice, which indicates the behavior of an adopter. In any given year, the adopter can completely drop out of adoption, reduce the usage of hybrid seed, use the same amount of hybrid seeds, or increase the usage. The independent variables include production related variables, such as total acres of land available, the use of fertilizer, and an indicator of whether a tractor was used to prepare the land. As weather has a significant impact on crop yields, annual rainfall is also included. Infrastructure variables, such as the distance to market and extension services, are also included. Finally, we include demographic information about each household head's gender, age, and education.

In table 2.3, adoption rates for hybrid seed are shown by agro-ecological region and years. Overall, the adoption rates increased from 63.8% in mid 90's to 71.6% in 2000, which is more than a 10% increase. The adoption rates were high in weather favorable zones, like Highlands and High Potential Maize Zone. The adoption rates were much lower in weather unfavorable zones, like Lowlands. The usage of hybrid seeds in kilograms per adopter is also shown in table 2.3. It seems that the higher rate of adoption the high usage of hybrid seeds, suggesting that new adopters may be cautious about the hybrid performance and plant small areas.

Figure 2.1 illustrates the average amount of hybrid seeds used from smallholders on a yearly basis. After a slight drop from 1996 to 1997, the usage increased from 1997 to 2000. In figure 2.2, on the other hand shows the average amount of hybrid seeds used from smallholders that adopted hybrid seeds in all four periods. After a slight drop from 1996 to 1997, the usage increased significantly from 1997 to 2000, suggesting that repeated adopters increase area planted after first adoption.

2.5 Empirical Results

Table 2.4 reports the results of random effects logit model coefficients estimation (equation 3) under the panel data assumptions. Under the random effects panel data assumption, we allow error terms to be correlated for the same smallholder during different periods through ρ. However, observations are assumed to be independent between different smallholders. The dependent variable, adoption, is equal to 1 if smallholder adopted hybrid seed in a given year and 0 if not. Results indicate that the size of the land, annual rainfall amount in the previous year, household head being male, usage of fertilizers, and using a tractor to prepare land contribute positively and significantly to the probability to adopt hybrid seeds. Distance to market contributes negatively and significantly to the probability to adopt hybrid seeds.

Next, we examine the behavior of initial adopters of hybrid seeds. After adoption in year one, an adopter has four choices for using hybrid seeds in the next year. He or she can drop adoption (choice=0), reduce the usage of hybrid seeds (choice=1), keep the same level of usage of hybrid seeds (choice=2), or increase the usage (choice=3). This pattern fits an ordered outcome models. We use the ordered logit model with cluster (on householder id) sandwiched estimator method and results are shown in table 2.5. The coefficients of the land available for cultivation and using fertilizer are positive and significant, while lack of credit and a longer distance to the market are negatively related to the adoption retention. Thus the availability of better financial institutions and infrastructure may be important in retaining and increasing adoption of improved technologies. Marginal effects can vary within different categories and we report marginal effects for increase hybrid seed usages (choice 3) in table 2.5.

We also examine the intensity usage of hybrid seeds (in kg) for adopters. However, because non-adopters do not use any hybrid seeds, there are lots of zeros in the dependent variables. Thus, we use the Tobit model censoring at zero with cluster (on householder id) sandwiched estimator method. Table 2.6 shows the results of the Tobit model. Results suggest that total acreage of available land, rainfall, gender of male, fertilizer use, and the use of tractor to prepare the land contribute positively and significantly to using more hybrid seeds. Needs for credit and the distance to market contribute negatively and significantly to use more hybrid seeds. If a smallholder needs credit, he or she will use on average 2.40 kgs less hybrid seeds holding everything else constant. For each mile away from the market, a smallholder will use 0.25 kg less hybrid seeds on average holding everything else constant.

We use the Tobit model to quantify the amount of hybrid seeds a smallholder uses. The conditional mean of hybrid seeds usage per smallholder is 9.75 kgs and the unconditional mean is 7.07 kgs. But, the Tobit model has the limitation that a coefficient must have the same sign of the marginal effect of using hybrid seeds and the marginal probability to adopt hybrid seeds.

As mentioned above, the two-tier Double Hurdle model is more flexible than the Tobit model. The Double Hurdle model assumes that a smallholder needs to cross two hurdles to be an adopter. The smallholder must cross the first hurdle to become a potential adopter. He or she must cross the second hurdle to become an adopter. In each hurdle equation, we allow error terms to be correlated for the same smallholder during different periods using the cluster (on householder id) sandwiched estimator method. But, observations are assumed to be independent between different smallholders. Also, the error terms from the first and second hurdle equation are assumed to be independent. The results of the equations for the first hurdle and the second hurdle are shown in table 2.7.

As mentioned, smallholders must pass the first hurdle to be a potential adopter. Both access to extension service and market contribute negatively and significantly to the probability to be a potential adopter (i.e. passing the first hurdle). Perhaps, the extension service center can provide more information about the adoption of hybrid seeds, thus it can convert more non-adopters to be potential adopters. Restrictions on credit do not play an important role in the first hurdle, as its coefficient is not significant. Usage of fertilizers makes a smallholder more likely to be a potential adopter. From equation (12), the average percentage of potential adopters is 59.1%. A potential adopter needs to pass the second hurdle to be an adopter. In table 2.7, the Tobit model in the presence of a first hurdle shows that need for credit plays an important and negative role when the potential adopter decides to adopt and on the intensity of use of hybrid seeds. Without enough cash, the potential adopter may not be able to buy hybrid seeds. Total acreage of land, rainfall, household head being male, and usage of tractor all contribute positively and significantly in the second hurdle. The conditional mean of hybrid seed usage per smallholder is 4.69 kgs (equation 15) and the unconditional mean (equation 16) is 1.92 kgs. The likelihood ratio test (LR) is 126.8 with df = 16. The LR is rejected at α=0.01 level and the test result rejects the Tobit model in favor of the Double Hurdle Model. It seems that the Double Hurdle model is a better model in this case compared to the Tobit model.

The Box-Cox double hurdle model transforms the dependent variable to hold the normality assumptions of the error term using cluster (on householder id) sandwiched estimator methods. Results in table 2.8 suggest that restrictions on access to extension service, and market contribute negatively and significantly to the probability to be a potential adopter. Usage of fertilizers and tractor, favorable rainfall, and being a male contribute positively and significantly to the probability to be a potential adopter. For the Tobit component, total land available, favorable rainfall, and using tractor will increase the usage of hybrid seeds for a smallholder. The restrictions on credit decrease the usage of hybrid seeds for a smallholder. However, the distance to extension service decreases the usage of hybrid seeds. The λ indicates the power to which all data should be raised. It is 0.15 and is significant. The likelihood ratio test is 191.6 with df =2, as we need to estimate λ in the Box-Cox double hurdle model. The LR is rejected at α=0.01 level; the test result shows that the Box-Cox double hurdle model is better than the standard double hurdle model.

2.6 Conclusions

Using the Kenya rural survey of 1996, 1997, 1998, and 2000, we study the production decisions with regards to hybrid seeds made by small-scale agricultural producers in Kenya. We find that easy access to market and improvement in extension service will help smallholder farmers to adopt hybrid seeds. If a smallholder has already adopted some kind of technology, such as using a tractor to prepare land or using fertilizer, he or she will be strongly inclined to adopt hybrid seeds.

We also study the behavior of initial adopters, which are mostly ignored by previous empirical studies. We find that credit restrictions and distance to market are the main barriers for initial adopters to increase usage of hybrid seeds.

To quantify smallholder's usage of hybrid seeds, we use the Tobit model, Double Hurdle model, and Box-Cox transformed Double Hurdle model. The Tobit is nested under the Double Hurdle model and it restricts a coefficient to have the same sign of marginal effect of usage and marginal probability of adoption. The Box-Cox transformed Double Hurdle model is introduced to hold the assumptions that the error terms of two hurdle equations are normal distributed. Based on the likelihood ratio tests, the Box-Cox transformed Double Hurdle model seems to be the best. For a smallholder to be a potential adopter, easy access to extension service and easy access to market are very important. Once the smallholder decides which quantities of hybrid seeds to use, he or she still faces the restriction on credit.

Our finds suggest that there is a trend that more smallholders adopt hybrid seeds and at the same time adopters increase the usage of hybrid seeds. In order to increase the adoption of hybrid seeds in sub-Saharan Africa, governments should increase extension service, improve access to market, and provide small loans to smallholders.

Table 2.1: Annual rainfall (mm) by agro-ecological zone and year

Agroecological zone	1996 rainfall	1997 rainfall	1998 rainfall	2000 rainfall
Central Highlands	786	1651	1331	477
Eastern Lowlands	640	1052	1030	456
High Potential Maize Zone	1163	1227	1180	910
Western Highlands	2045	1645	1504	1625
Western Lowlands	1598	1565	1262	1170
Western Transitional	1853	1673	1649	1711
All Zones	1259	1460	1306	969

Table 2.2: Summary Statistics

Variable	Description	1996		1997		1998		2000	
		Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Adopt	1=householder adopted hybrid seeds, otherwise =0 if household dropped household dropped adoption; (binary)	0.641	0.482	0.633	0.482	0.664	0.467	0.719	0.436
Choice	=0 if dropped adoption; =1 if household reduced usage of hybrid seeds; =2 if household had same usage of hybrid seeds; =3 if household increased usage of hybrid seeds			1.842	0.763	1.838	1.051	1.812	1.101
Acres	Total acres of land householder has to plant crops	3.494	2.887	3.668	3.549	3.810	2.852	4.536	5.193
Rainfall	Total annual rain fall in the previous year (in 1000mm)	1.258	0.530	1.460	0.315	1.306	0.219	0.969	0.521
Fertilizer	1=householder used fertilizer; 0 otherwise (binary)	0.710	0.462	0.732	0.436	0.702	0.458	0.812	0.392

Tractor	1=householder used tractor 0 otherwise (binary)	0.159	0.368	0.153	0.363	0.162	0.368	0.172	0.373
Creditry	1=householder applied for credit in that year; 0 otherwise (binary)	0.501	0.501	0.500	0.503	0.419	0.494	0.587	0.493
Distance to Market	Distance to market (km)	6.194	7.588	6.182	7.576	5.972	6.683	4.444	5.762
Distance to Extension	Distance from extension service (km)	5.162	3.879	5.154	3.872	5.163	3.885	4.932	4.191
Gender	Sex of household head. 1= male 0= female (binary)	0.687	0.455	0.691	0.462	0.691	0.462	0.691	0.462
Age	Age of household head	47.041	15.112	48.041	15.112	49.041	15.112	51.04	15.112
Education	Years of schooling of household head	5.972	4.264	5.972	4.264	5.972	4.264	5.972	4.264
Number of observations	1840								
Number of HHID	460								

Table 2.3: Percentage of household that adopted hybrid seeds and quantity of hybrid seeds used, by agro-ecological zone and year

Agroecological zone	1996		1997		1998		2000	
	Adoption %	hybrid seeds kgs	adoption %	hybrid seeds kgs	adoption %	hybrid seeds kgs	adoption %	hybrid seeds kgs
Central Highlands	88.5%	5.3	87.6%	5.6	88.5%	4.8	87.6%	4.9
Eastern Lowlands	17.4%	1.1	23.2%	1.6	27.5%	1.7	27.2%	4.3
High Potential Maize Zone	92.3%	14.1	92.3%	14.5	97.1%	16.1	94.5%	16.9
Western Highlands	76.7%	5.2	65.0%	4.4	71.7%	6.0	71.7%	5.5
Western Lowlands	4.2%	0.3	7.1%	0.4	12.9%	1.1	14.6%	2.0
Western Transitional	78.0%	10.3	72.9%	8.1	72.9%	7.7	79.7%	7.7
All Zones	63.8%	6.5	62.7%	6.4	66.2%	6.8	71.6%	9.6
Observations	1840							

Table 2.4: Logit model of adoption of hybrid seeds

	Hybrid Seed Adoption	
Variables	Coefficients	Robust standard Error
Acres	0.067	0.040*
Rain	0.843	0.323**
Gender	1.375	0.403***
Education	0.029	0.050
Age	0.011	0 .013
Fertilizer	2.393	0.307***
Tractor	2.935	0.584***
Creditry	-0.070	0.271
Distance to Market	-0.127	0 .023***
Distance to Extension	-0.045	0.038
Year 96	-1.025	0.310***
Year 97	-1.279	0 .337***
Year 98	-0.892	0.313**
constant	-1.550	0.944
σ_u^2	2.683	0.264
ρ	0.683	0.042
Number of Households	441	

***Significant at α=0.01

**Significant at α=0.05

*Significant at α=0.10

Table 2.5: Ordered logit model for adopter's choice

Variables	Coefficients	Standard Error	Marginal Effect	Standard Error
Acres	0.056	0.026**	0.012	0.006**
Rain	-0.091	0.191	-0.019	0.041
Male	0.005	0.158	0.001	0.034
Education	0.004	0.017	0.001	0.004
Age	-0.005	0.006	-0.001	0.001
Fertilizer	1.159	0.292***	0.201	0.047***
Tractor	0.160	0.167	0.035	0.037
Creditry	-0.358	0.134**	-0.077	0.029**
Distance to Market	-0.038	0.015*	-0.008	0.003**
Distance to Extension	0.008	0.015	0.002	0.003
Year 97	0.033	0.195	0.007	0.042
Year 98	0.005	0.225	0.001	0.048
Number of Households	309			

***Significant at α=0.01

**Significant at α=0.05

*Significant at α=0.10

Table 2.6: Tobit model for hybrid seed usage (kgs)

	Hybrid Seed Usage	
Variables	Coefficients	Robust standard Error
Acres	0.320	0.088 ***
Rain	2.780	0 .780 ***
Male	2.215	0.880 ***
Education	0.014	0.090
Age	0.037	0.025
Fertilizer	7.745	0.930 ***
Tractor	9.733	0.849 ***
Creditry	-2.404	0.676 ***
Distance to Market	-0.249	0.054 ***
Distance to Extension	-0.008	0.088
Year96	-2.305	0.624 ***
Year97	-3.254	0.725 ***
Year98	-2.927	0.622 ***
cons	-6.237	2.053
Number of Households	441	
Log Likelihood	-4061.6	

***Significant at α=0.01

**Significant at α=0.05

*Significant at α=0.10

Table 2.7: Double hurdle model for hybrid seed usage (kgs)

	First Hurdle		Tobit Model	
Variables	Coefficients	Robust standard Error	Coefficients	Robust standard Error
Acres	-0.006	0.020	0.324	0.097 ***
Rain	0.478	0.324	2.533	0.760 ***
Male	0.566	0.246 **	1.345	0 .896
Education	-0.037	0.030	0.072	0.089
Age	-0.002	0.010	0.050	0.026 *
Fertilizer	3.512	1.119 ***	0.413	1.443
Tractor	0.132	0.358	9.636	0 .802 ***
Creditry	-0.007	0.302	-2.657	0.696 ***
Distance to Market	-0.079	0.019 ***	-0.050	0.067
Distance to Extension	-0.055	0.028 **	0.079	0.093
Year96	-0.854	0.470 *	-1.281	0.664 *
Year97	-0.625	0.478	-2.656	0.755 ***
Year98	-0.628	0.436	-2.251	0.617 ***
cons	0.592	0.702	0.330	2.348
Number of Households	441			
Log Likelihood	-3998.2			

***Significant at α=0.01

**Significant at α=0.05

*Significant at α=0.10

Table 2.8: Box-cox double hurdle model for hybrid Seeds usage (kgs)

	First Hurdle		Tobit Model	
Variables	Coefficients	Standard Error	Coefficients	Standard Error
Acres	0.003	0.012	0.055	0.017 ***
Rain	0.364	0.127 ***	0.285	0.095 **
Male	0.353	0.126 ***	0.055	0 .117
Education	0.003	0.014	0.009	0.013
Age	0.005	0.004	0.003	0.004
Fertilizer	1.195	0.110 ***	-0.041	0.121
Tractor	1.106	0.173 ***	1.081	0 .113 ***
Creditry	-0.146	0.108	-0.350	0.093 ***
Distance to Market	-0.044	0.008 ***	0.009	0.007
Distance to Extension	-0.029	0.013 **	0.030	0.012 **
Year96	-0.422	0.108 ***	-0.023	0.083
Year97	-0.512	0.123 ***	-0.144	0.094
Year98	-0.413	0.120 ***	-0.223	0.081 ***
cons	-0.613	0.291	1.517	0.292
λ	0.166	0.036 ***		
σ	1.008	0.074 ***		
Number of Households	441			
Log Likelihood	-3902.4			

***Significant at α=0.01

**Significant at α=0.05

*Significant at α=0.10

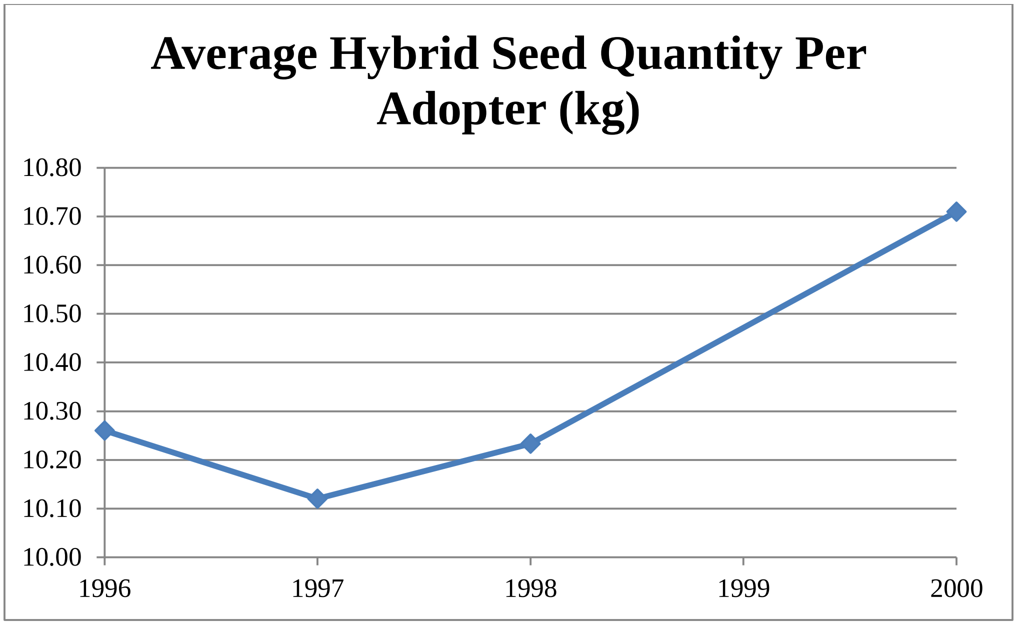


Figure 2.1: Average hybrid seeds usage (kgs) for a smallholder

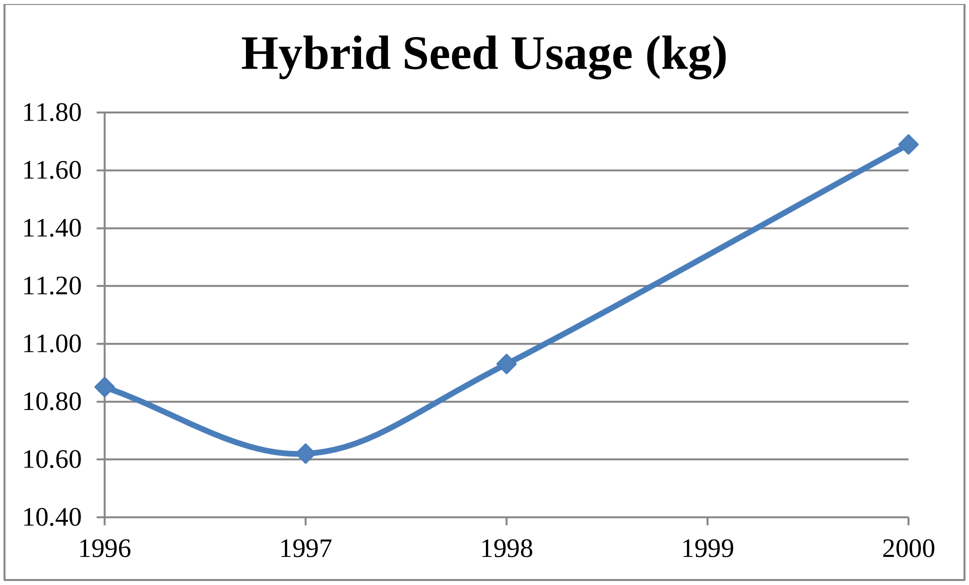


Figure 2.2: Hybrid seeds usage (kgs) from smallholders adopting in all four periods

CHAPTER 3

Pre and Post Recession Input Allocation Decisions of Farm Credit System Lending Units

3.1 Introduction

As a government sponsored enterprise, FCS is a network of borrower-owned financial institutions to provide credit and financial services to farmers, ranchers, producers or harvesters of aquatic products, and agricultural and aquatic cooperatives. The system raises funds by selling securities in the national and international money markets. In 2013, FCS had more than $260 billion assets and nearly 500,000 member borrowers. Unlike commercial banks, FCS lending units are not depository institutions and rely on the U.S. and international capital market to raise funds by issuing system-wide debt notes and bonds. As of January 2013, FCS is composed of four banks and 82 associations (see FCS annual report 2013). The banks of FCS provide loans to its affiliated associations (i.e. FCS lending associations), while such associations make short, intermediate, and long term loans to qualified borrowers. FCS provides more than $191 billion loans, which consist of more than one third of the credit needed by American people living and working in rural areas. The system's goal is to meet a broad range of public needs by maintaining liquidity and competition in rural credit markets in both good and bad economic conditions.

The 2007-2009 global recession was sparked by the outbreak of the U.S. subprime mortgage and financial crisis. It resulted in the threat of total collapse of financial markets, the expensive bailout of banks by national governments, and the plummet of stock markets around the world. The global recession reduced the demand of farm products, causing declining commodity prices. Thus, this raised the risk environment of the FCS. Although FCS banks and associations maintained a capital ratio above the minimum regulation requirements, the turmoil in the U.S. and global markets during the recession limited the System's ability to raise third-party capital or issue term debt.

In this paper, we analyze the efficiencies of FCS lending units before and after the 2007-2009 recessions. A specific focus of the analysis is the input allocation decisions and strategies of FCS lending units during the study period. The lending units are analyzed and compared according to their types of operations (banks versus credit associations) as well as different size categories.

3.2 The Theoretical Model

The Technical Efficiency Model

The stochastic frontier model is used in a large literature of studies of production, cost, revenue, profit and other models of goals. The model was first introduced by Aigner, Lovell, and Schmidt (1977). 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):

$$(1)\quad D^I(\mathbf{x}, \mathbf{y}) = \sup_{\rho}\{\rho > 0 : (\mathbf{x}/\rho) \in L(\mathbf{y})\}$$

where the superscript I implies that it is the input distance function; the input set $L(\mathbf{y}) = \{\mathbf{x} \in \mathbf{R}_N^+ : \mathbf{x}$ 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 reduction 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 without price information and whenever the cost minimization or revenue maximization assumptions are inappropriate. This analytical framework applies well to Farm Credit System's operations since their operations are often characterized by multi-inputs and multi-outputs. Moreover, the lending units usually have greater control over operating inputs instead of their outputs.

This analysis adopts the Translog function that overcomes the shortcomings of the usual Cobb-Douglas functional form, which assumes that all firms have the same production elasticities, which sum up to one. The Translog function is more flexible with fewer restrictions on production and substitution elasticities. The flexibility reduces the possibility of producing biased estimates because of erroneous assumptions on the functional form.

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

(2)
$$
\begin{aligned}
\ln D_{it}^{I} = {} & \beta_0 + \sum_{k=1}^{M} \beta_{y_k} \ln y_{ikt} + \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M} \beta_{y_{kl}} \ln y_{ikt} \ln y_{ilt} + \sum_{j=1}^{N} \beta_{x_j} \ln x_{ijt} + \frac{1}{2}\sum_{j=1}^{N}\sum_{h=1}^{N} \beta_{x_{jh}} \ln x_{ijt} \ln x_{iht} \\
& + \sum_{j=1}^{N}\sum_{k=1}^{M} \beta_{xy_{jk}} \ln x_{ijt} \ln y_{ikt} + \sum_{d=1}^{P} \beta_{z_d} \ln z_{idt} + \frac{1}{2}\sum_{d=1}^{P}\sum_{f=1}^{P} \beta_{z_{df}} \ln z_{idt} \ln z_{ift} + \sum_{k=1}^{M}\sum_{d=1}^{P} \beta_{yz_{kd}} \ln y_{ikt} \ln z_{idt} \\
& + \sum_{j=1}^{N}\sum_{d=1}^{P} \beta_{xz_{jd}} \ln x_{ijt} \ln z_{idt} + \sum_{k=1}^{M} \alpha_k (t \ln y_{ikt}) + \sum_{j=1}^{N} \delta_j (t \ln x_{ijt}) + \sum_{d=1}^{P} \theta_d (t \ln z_{idt}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
& + \sum_{g=1}^{G-1} d_g dum_{igt} + d_a dum_{iat} + d_b dum_{ibt}
\end{aligned}
$$

where $dum_{g,it}$ is the dummy variable to present the agency size in group ; g=1,…(G-1) and G=5 (number of groups); k, l = 1, … M and M = 3 (number of outputs); j, h = 1, … N and N = 3 (number of inputs); d, f = 1, … P and P = 2 (number of indexes to measure financial risks and loan's quality); t is the quarter index during time periods. The dum_{iat} is a dummy variable, which is 1 for FCS banks and 0 for associations; the dum_{ibt} is the dummy variable, which is 0 for periods before the recession.

A necessary property of the input distance function is homogeneity of degree one in input quantities, which required the parameters in equation (2) to satisfy the following constraints:

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

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

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

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

$$\sum_{j=1}^{N} \delta_j = 0 \tag{R5}$$

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

$$(3)\ \ D_{it}^{I}(\lambda \mathbf{x}, \mathbf{y}) = \lambda D_{it}^{I}(\mathbf{x}, \mathbf{y}), \qquad \forall \lambda > 0\,.$$

Assuming that $\lambda = 1/x_{N,it}$ [1], equation (3) can be expressed in the logarithmic form as:

$$(4)\ \ \ln D_{it}^{I}(\mathbf{x}/x_{N,it}, \mathbf{y}) = \ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) - \ln x_{N,it}$$

[1] 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).

According to the definition of the input distance function, the logarithm of the distance function in (4) measures the deviation (ε_{it}) of each observation $(\mathbf{x},\mathbf{y})$ from the efficient production frontier $L(\mathbf{y})$:

(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:

(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 pure random error that follows the normal distribution as $v_{it} \overset{iid}{\sim} N(0,\sigma_v{}^2)$.

Substituting equation (6) into equation (4), equation (4) can then be rewritten as:

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

Besides the homogeneity restrictions, the symmetric restrictions also need to be imposed when to estimate the Translog input distance function. The symmetric restrictions require the parameters in equation (2) should satisfy the following constraints:

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

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

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

Imposing restrictions (R1) through (R8) and equation (2) upon equation (7) yields the estimating form of the input distance function as follows:

(8)

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

where $x_{j,it}{}^{*} = x_{j,it} / x_{N,it}$ is the normalized input *j*. For the general model form, the inefficiency effects can be modeled as

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

where $u_i \overset{iid}{\sim} N^{+}(\mu, \sigma_\mu^2)$. Since our model is estimated for panel data, the hypothesis of time-invariance $(\eta = 0)$ needs to be tested. 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 (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 (8), the coefficients for the N^{th} input can be calculated by imposing the homothetic restrictions (R1) to (R5).

Efficiency Measures

Efficiency can be decomposed into two separate components: technical efficiency (TE) and allocative efficiency (AE). Unfortunately, as Bauer (1990) has pointed out, it is difficult to obtain separate TE and AE measures. Figure 3.1 will help understand the mechanics of such decomposition. In the plots, we assume a firm that uses two inputs (x_1 and x_2) 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 $TE = OC / OA$. Recalling the definition of the input distance function, the following linkage can be established between $D^I(\mathbf{x}, \mathbf{y})$ and *TE*.

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

Given the input prices p_1 and p_2, the AE concept can also be illustrated in figure 3.1. 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

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

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

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

$\eta = 0$ 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 shadow prices. Initially, the studies were based on the estimation of the system equations composed by cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, the validation of this system equations' estimation requires the assumption of the cost minimization. Recently, some researchers provided an alternative method to get shadow prices out of inputs using Shephard's distance function (Fare and Grosskopf, 1990; Banos-Pino et al., 2002; Atkinson and Primont, 2002; Rodriguez-Alvarez et al., 2004). Under this new analysis scheme, the assumption of the cost minimization is not necessary to get the consistent estimates. They allow the difference between the market prices and shadow prices with respect to the minimum costs. As illustrated for simplified situation by figure 3.1, shadow price ratio p_1^s / p_2^s is the slope of the isocost curve *f3* which indicates the minimum cost at given level of inputs to produce the same quantity of the outputs. In other words, a firm would be allocative efficient if it could operate at point C which is on the isocost curve f_3 to satisfy the condition required by the 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 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 the allocative inefficiency. The ratio can be expressed as $k_{12} = \dfrac{p_1^s / p_2^s}{p_1 / p_2}$

. Specifically, if the ratio equals to 1, the allocative efficiency achieved. Otherwise, the allocative inefficiency is detected. The larger does $|k_{12}|$ deviate from 1, the larger allocative inefficiency is.

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):

$$\text{(12)}\quad k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p_{j,it}{}^s / p_{j,it}}{p_{h,it}{}^s / p_{h,it}} = \frac{p_{j,it}{}^s}{p_{h,it}{}^s} \cdot \frac{p_{h,it}}{p_{j,it}}$$

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:

$$\text{(13)}\quad C(\mathbf{y}, \mathbf{p}) = \min_{\mathbf{x}} \{\mathbf{px} : D(\mathbf{y}, \mathbf{x}) \geq 1\}$$

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:

$$\text{(14)}\quad \frac{\partial D_{it}^I(\mathbf{x}, \mathbf{y})}{\partial x_{j,it}} = \frac{p_{j,it}^s}{C(\mathbf{y}, \mathbf{p}^s)}.$$

From equation (14), the ratio of the shadow prices can be calculated as:

$$(15)\quad \frac{p_{j,it}{}^{s}}{p_{h,it}{}^{s}} = \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial x_{j,it}}{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial x_{h,it}}$$

Applying the derivative envelope theory to the numerator and denominator of equation (15) results in the following:

$$(16)\quad \begin{aligned} \frac{p_{j,it}{}^{s}}{p_{h,it}{}^{s}} = \frac{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial x_{j,it}}{\partial D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial x_{h,it}} &= \frac{\left[1 \big/ \left(D_{it}^{I}(\mathbf{x},\mathbf{y}) \cdot x_{j,it}\right)\right] \cdot \left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}\right]}{\left[1 \big/ \left(D_{it}^{I}(\mathbf{x},\mathbf{y}) \cdot x_{h,it}\right)\right] \cdot \left[\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}\right]} \\ &= \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}}{\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}} \end{aligned}$$

Finally, substituting equation (16) into equation (12), the relative allocative inefficiency shown by the relative input price correction indices can then be expressed as:

$$(17)\quad \begin{aligned} k_{jh,it} &= \frac{p_{h,it}}{p_{j,it}} \cdot \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}}{\partial \ln D_{\mathrm{it}}^{I}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}} \\ &= \frac{p_{h,it} x_{h,it}}{p_{j,it} x_{j,it}} \cdot \frac{\beta_{x_j} + \sum_{h=1}^{N} \beta_{x_{jh}} \ln x_{h,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t}{\beta_{x_j} + \sum_{j=1}^{N} \beta_{x_{jh}} \ln x_{j,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t} \end{aligned}$$

3.3 Data

This study collected quarterly panel data from the Call Report Database from 2005 to 2011 published online by the Farm Credit Administration. The numbers from the original data are CPI adjusted with year 2005 as the baseline. It is important to use the real dollars because this will allow us to make more accurate year-to-year comparison of efficiencies. There are a total of 5 FCS banks and more than 100 credit associations that altogether produce 2,913 observations across 7 years. Lending institutions are classified as banks and associations. They are also classified into 5 groups based on total assets size. The size categories were determined as follows: lenders with total assets of less than \$1 billion are grouped under Group 1; Group 2 lenders have assets between \$1 billion and \$2 billion; Group 3 lenders' assets range from \$2 billion to \$5 billion; Group 4 lenders' total assets are between \$5 billion and \$10 billion; and the largest lenders fall under Group 5 with assets over \$10 billion.

Lending institutions output data collected include agricultural loans (y1), non-agricultural loans (y2), and other assets (y3). Input data are labor (x1), physical capital (x2), and financial capital (x3). Unlike commercial banks, FCS lending units do not have direct deposits as a source of financial capital. FCS banks raise capital from the financial markets and loan to credit associations.

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 lending units' loan portfolios (Stiroh and Metli, 2003). The index z_2 is based on the lending units' capital to asset ratio, which is used in this study 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 et al., 2001). Actually, as a supplemental funding source to liabilities, equity capital can provide a cushion to protect banks from loan losses and financial distress. Lending units with lower capital to asset ratios (CAR) would be inclined to increasingly rely on debt financing, which, in turn, increases the probability of insolvency.

The summary statistics are reported in table 3.1.

3.4 Empirical Results

The coefficient estimates of the components of the input distance function (defined in equation 8) are summarized in table 3.2. The hypothesis that all coefficients of the distance function are equal to zero is rejected at the 0.01 level by an LM test (p-value<.0001). The hypothesis that the function takes a Cobb-Douglas form, which requires that all parameters except for β_{y_k} and β_{x_j} in equation (2) equals to 0, is rejected at 1% level by the LM test. This result suggests that the flexible Translog function form is more applicable than the Cobb-Doublas function form (Dang and Leatham, 2011) in this study.

The coefficient of the dummy variable dum_{iat} that captures the effect of lender type is significantly different from 0 at 1% level. This indicates that differences in operating structure between FCS banks and credit associations can influence the cost structure of these lenders. On the other hand, the time dummy dum_{ibt} that separates the time period into the pre-recession and recession phases is also significant level at 1%, thereby suggesting a notable change in efficiency levels during the recession.

The t statistics for η given in table 3.2 shows a significant result (P-value<.0001), which indicates that the hypothesis of a time-invariant model is rejected in favor of a time-variant model. This allows the system to face a time-variant technical efficiency level from 2005 to 2011. The sign of η is slightly negative and suggests that the efficiency of FCS lending units was deteriorating.

Overall Technical Efficiency

Table 3.3 shows the mean Technical Efficiency (TE) levels for the different lending units and size categories. The summary also includes the results of t-tests conducted on the differences between pairings of annual TE results from different groups.

The results indicate that the overall TE levels of both FCS banks and credit associations are below 1, thereby suggesting that these lenders in general have been operating below efficiency during the sample period. The mean TE level for FCS banks is 9% while the credit associations posted a mean TE level of 33%. According to the t-test result, these TE results are significantly different from one at 1% level. These results are further confirmed by a visual representation of the results through the plots presented in Figure 3.2. We find that TE level is improving, though not significantly, for both FCS banks and credit association. Those results can also be confirmed by the improvement of financial strengths of lending units from FCS annual reports from 2005 to 2011.

Table 3.3 shows that lenders' size can also be an important factor that can influence the TE levels of the lenders. Based on the summary in that table, all size categories registered TE levels below 0.50 during the sample period. However, among these size categories, the smaller lenders tend to have relatively higher TE levels than the larger lenders. These results are also shown in figure 3.3. The pairwise differences in TE levels have been found to be significant for all different groups.

Input Allocation Decisions

As explained earlier in the theoretical model, $k_{jh,it}$ calculated by equation (17) can be used to measure the relative allocative inefficiency level. Tables 3.4 and 3.5 present a summary of the average values of the k_{jh} (input allocation ratios) for the different lending units and size categories. Figure 3.4 provides a comparison of the plots of input allocation ratios (k_{jh}) of FCS banks and credit associations.

The k_{12} ratio is the input allocation ratio between labor and physical capital. Inputs are most efficiently used if the ratio is equal or closer to one. In figure 3.4, both of the FCS banks and credit associations' k_{12} results lie above the critical boundary (k_{12} =1). These results indicate that FCS lending units over utilized their physical assets while underutilizing their labor inputs.

For k_{13} (labor vs. financial assets), FCS banks' ratio lie above the critical boundary (=1) from 2005 to 2010 and the ratio is just below 1 in 2011. Credit associations' k_{13} ratios lie below the critical boundary (=1). These results indicate that banks over utilized their financial inputs most of the time and credit associations over utilized their labor.

For k_{23} (physical assets vs. financial assets), FCS banks' ratios lie above the critical boundary (=1). The credit associations' k_{13} ratios lie above 1 during the recession and lie below 1 after the recession. These results indicate that FCS banks over utilized their financial inputs. Credit Associations over utilized financial inputs during the recession and over utilized physical assets after the recession. There are spikes of the k_{12} and k_{13} ratios for FCS banks during the recession. FCS Banks raise capital for associations through domestic and global money market. It was hard to get capital during the recession and banks had to over utilize their existing financial assets. The ratios went down significantly after the recession, suggesting improving capital market conditions.

Figure 3.5 shows the graphs for the different input allocation ratios (k_{jh}) for the various lender size categories. The plots of the k_{12} ratios indicate that smaller lenders (group 1) tend to over-utilize their labor inputs vis-a-vis their physical capital given that $k_{12} < 1$ consistently through all seven years. On the other hand, larger lenders over-utilize their physical capital inputs vis-a-vis their labor inputs. These results indicate that smaller lenders may have resorted to exhausting their labor to cope with increasing competitive pressure from the larger lenders.

The plots of the k_{13} ratios indicate that all lending units tend to over-utilize their labor inputs vis-a-vis their financial capital given that $k_{13} < 1$ consistently through all seven years. The results for the k_{13} ratios also show that all size categories have shown tendencies to increase this ratio before the recession and then making adjustments in their operating decisions to bring down the ratio afterwards. Compared to big size groups, smaller lenders (group 1) dropped the k_{13} ratios more significantly after the recession.

Generally, all lender groups underutilized their physical capital inputs vis-a-vis financial inputs ($k_{23} > 1$) before the recession. The results for the k_{13} ratios also show that all size categories have shown tendencies to decrease this ratio during and after the recession. All lending units made adjustments in operating decisions and brought this ratios more close to the efficiency line ($k_{23} = 1$).

3.5 Conclusions

As a major supplier of farm credit, Farm Credit System (FCS) lending units have long been serving the agricultural industry. After the economic crises hit the nation and the global community in the late 2000s, the farm lending sector emerged as one of the notable survivors, registering a very minimal rate of institutional failure while the rest of the industry was dealt with more significant blows in alarming rates of bank failures and borrower delinquencies. Some analysts have recognized farm borrowers for their impressive minimal loan delinquency record (compared to borrowers from other industries) that has been maintained before, during and after the recessionary period.

This study provides an additional perspective in explaining the farm credit systems lending units' performance during the last recession. The overall results of technical and allocative efficiency analyses confirm that both FCS banks and credit associations are plagued with higher costs that could diminish their overall levels of efficiency. However, this liability does not need to constrain these lenders' capability to operate successfully even under a period of recession. The key strategies to these lenders' survival are their input allocations decisions.

This study's results show that the overall TE level of both FCS banks and credit associations (ACA) are below efficiency. Credit associations are more efficient than banks. Small lenders tend to have relatively higher TE than larger lenders. For input allocative ratio k_{12} (labor vs. physical assets), banks and associations over utilized physical assets compared to labor. For ratio k_{13} (labor vs. financial assets), FCS banks over utilized financial inputs and credit associations over utilized labor. For k_{23} (physical assets vs. financial assets), FCS banks over utilized their financial inputs and credit associations over utilized financial inputs during the recession and over utilized physical assets after the recession. FCS lending units do not have deposits as a source of capital and rely on banks to raise funds in the money market. FCS Banks over utilized existing financial assets during the recessions, as they were hard to get capital from the market.

Table 3.1. Summary Statistics of FCS Lending Units, 2005-2011

Variables	Sample Mean	Std. Deviation	Minimum	Maximum
Banks				
Agricultural Loans (y_1)	2,670,943	2,720,737	589	14,970,670
Non-Agricultural Loans (y_2)	20,980,380	14,274,330	73,124	53,897,990
Others (y_3)	124,800	191,916	6,538	1,116,259
Labor (x_1)	8,055	5,114	3,508	33,888
Physical Capital (x_2)	10,795	6,955	2,254	35,416
Financial Inputs (x_3)	28,001,370	17,723,550	8,577,538	72,917,860
Loan Quality Index (z_1)	0.0013	0.0022	0.0000	0.0100
Financial Risk Index (z_2)	0.9427	0.0115	0.9083	0.9585
Associations				
Agricultural Loans (y_1)	1,218,729	2,169,966	63	20,323,460
Non-Agricultural Loans (y_2)	328346	2583113	9	30,428,610
Others (y_3)	16,213	94,479	1	1,687,746
Labor (x_1)	2,860	4,378	100	36,721
Physical Capital (x_2)	5,843	10,507	140	105,511
Financial Inputs (x_3)	1,452,794	4,742,172	29,795	57,248,780
Loan Quality Index (z_1)	0.0073	0.0133	0.0000	0.1251
Financial Risk Index (z_2)	0.8220	0.0410	0.6454	0.9469

Table 3.2 Estimation Results for the Input Distance Function

Model Coefficients and Parameter Estimates							
Intercept	2.922*** (0.046)	$\beta_{y_{12}}$	-0.001 (0.001)	$\beta_{yz_{22}}$	-0.060** (0.018)	dum_{g_1}	0.155*** (0.017)
β_{y_1}	-0.060*** (0.008)	$\beta_{y_{13}}$	0.000 (0.001)	$\beta_{yz_{32}}$	0.069*** (0.019)	dum_{g_2}	0.104*** (0.010)
β_{y_2}	-0.049*** (0.005)	$\beta_{y_{23}}$	-0.005*** (0.001)	$\beta_{xz_{11}}$	-0.441** (0.184)	dum_{g_3}	0.054*** (0.007)
β_{y_3}	-0.006 (0.004)	$\beta_{x_{12}}$	0.001 (0.003)	$\beta_{xz_{21}}$	0.078 (0.119)	dum_{g_4}	0.016** (0.005)
β_{x_1}	0.084*** (0.009)	$\beta_{z_{12}}$	-5.911*** (1.673)	$\beta_{xz_{12}}$	0.170*** (0.045)	dum_{iat}	-0.765*** (0.107)
β_{x_2}	-0.008 (0.008)	$\beta_{xy_{11}}$	-0.014*** (0.001)	$\beta_{xz_{22}}$	0.209*** (0.044)	dum_{ibt}	0.013*** (0.003)
β_{z_1}	2.308*** (0.472)	$\beta_{xy_{12}}$	0.002* (0.001)	α_1	-0.007*** (0.0002)	d_b	0.012** (0.004)
β_{z_2}	-4.016*** (0.119)	$\beta_{xy_{13}}$	0.008*** (0.001)	α_2	0.0002** (0.0001)	η	-0.003*** (0.001)
$\beta_{y_{11}}$	-0.011*** (0.001)	$\beta_{xy_{21}}$	0.007*** (0.002)	α_3	-0.000 (0.0002)		
$\beta_{y_{22}}$	-0.006*** (0.001)	$\beta_{xy_{22}}$	0.000 (0.001)	δ_1	0.001** (0.0003)		
$\beta_{y_{33}}$	-0.003*** (0.001)	$\beta_{xy_{23}}$	-0.005*** (0.001)	δ_2	0.0002 (0.0002)		
$\beta_{x_{11}}$	0.013*** (0.004)	$\beta_{yz_{11}}$	-0.166 (0.205)	θ_1	-0.131*** (0.015)		
$\beta_{x_{22}}$	0.004 (0.005)	$\beta_{yz_{21}}$	-0.238*** (0.067)	θ_2	-0.005** (0.003)		
$\beta_{z_{11}}$	-12.102*** (3.765)	$\beta_{yz_{31}}$	0.080* (0.050)	λ_1	-0.030*** (0.002)		
$\beta_{z_{22}}$	-10.770*** (0.817)	$\beta_{yz_{12}}$	-0.040 (0.038)	λ_2	0.000*** (0.00003)		

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 3.3. Technical Efficiency Levels and Mean Differences, Comparison between FCS Banks and Credit Associations

Category	Estimate	Standard Errors	Pr > |t|	Number of Observations
By Type				
FCS Banks	0.09	0.034	<.0001	2816
Credit Associations	0.33	0.187	<.0001	130
Difference between Means	-0.24	0.005	<.0001	
By Size				
Group 1	0.83	0.107	<.0001	96
Group 2	0.61	0.115	<.0001	248
Group 3	0.40	0.081	<.0001	956
Group 4	0.27	0.059	<.0001	675
Group 5	0.13	0.062	<.0001	971
Difference between Means				
Group1-Group2	0.22	0.000	<.0001	
Group1-Group3	0.43	0.000	<.0001	
Group1-Group4	0.56	0.000	<.0001	
Group1-Group5	0.70	0.000	<.0001	
Group2-Group3	0.21	0.000	<.0001	
Group2-Group4	0.34	0.000	<.0001	
Group2-Group5	0.48	0.000	<.0001	
Group3-Group4	0.13	0.000	<.0001	
Group3-Group5	0.27	0.000	<.0001	
Group4-Group5	0.14	0.000	<.0001	

Table 3.4. Input Allocation Ratios (k_{jh}) by Lending Units Categories, Annual Averages, 2005-2011

Lending Units Categories	Year	k12[a]	k13[b]	k23[c]
FCS Banks	2005	2.39***	1.89***	2.59***
	2006	1.15***	2.97***	4.15***
	2007	2.10***	3.41***	4.21***
	2008	3.57***	2.47***	3.05***
	2009	1.67***	1.45***	2.10***
	2010	1.70***	1.13***	1.66***
	2011	2.11***	0.91***	1.31***
Credit Associations	2005	1.12***	0.33***	1.14***
	2006	1.33***	0.47***	1.49***
	2007	1.41***	0.53***	1.60***
	2008	1.57***	0.45***	1.13***
	2009	1.38***	0.33***	0.77***
	2010	1.39***	0.30***	0.68***
	2011	1.20***	0.25***	0.63***
Pair Wise t-test Between Groups[d]		-3.02***	-55.48***	-12.19***

Notes: [a] Input 1 is labor and input 2 is physical capital.
[b] Input 3 is financial inputs.
[c] k ratios significant different between groups are marked using “*”
[d] t value for difference test between FCS banks and Credit Associations
*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level

Table 3.5. Input Allocation Ratios (k_{jh}) by Group Categories, Annual Averages, 2006-2011

Bank Categories	Year	k12[a]	k13[b]	k23
Group 1	2005	0.89	0.36	1.09
	2006	0.96	0.42	1.50
	2007	0.76	0.44	1.61
	2008	0.54	0.38	1.24
	2009	0.73	0.28	0.85
	2010	0.80	0.30	1.03
	2011	0.44	0.06	0.14
Group 2	2005	1.53	0.36	1.29
	2006	1.11	0.50	1.88
	2007	1.18	0.55	1.86
	2008	1.90	0.50	1.54
	2009	1.03	0.46	1.12
	2010	1.33	0.39	0.66
	2011	0.91	0.34	0.79
Group 3	2005	1.20	0.34	1.20
	2006	1.33	0.48	1.62
	2007	1.38	0.56	1.90
	2008	1.53	0.49	1.22
	2009	1.32	0.36	0.78
	2010	1.39	0.34	0.70
	2011	1.23	0.28	0.63
Group 4	2005	0.94	0.33	1.10
	2006	1.28	0.50	1.38
	2007	1.43	0.56	1.24
	2008	2.13	0.44	0.88
	2009	1.61	0.31	0.79
	2010	1.09	0.29	0.75
	2011	1.35	0.24	0.72
Group 5	2005	1.23	0.55	1.26
	2006	1.46	0.79	1.68
	2007	1.64	0.85	1.80
	2008	1.54	0.66	1.33
	2009	1.45	0.43	0.84
	2010	1.69	0.36	0.71
	2011	1.29	0.30	0.62

Notes: [a] Input 1 is labor while input 2 is physical capital.
[b] Input 3 is financial inputs which include: purchased financial capital and deposit.

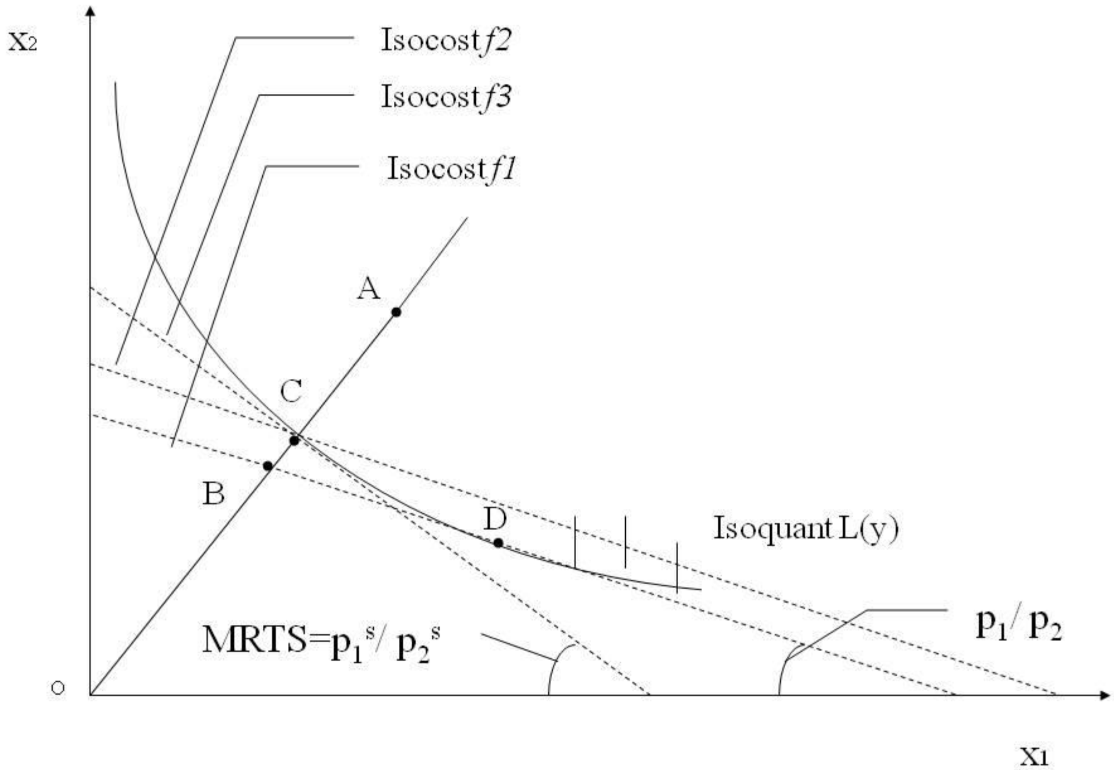


Figure 3.1: Technical and Allocative Efficiency Identified by Input Distance Function

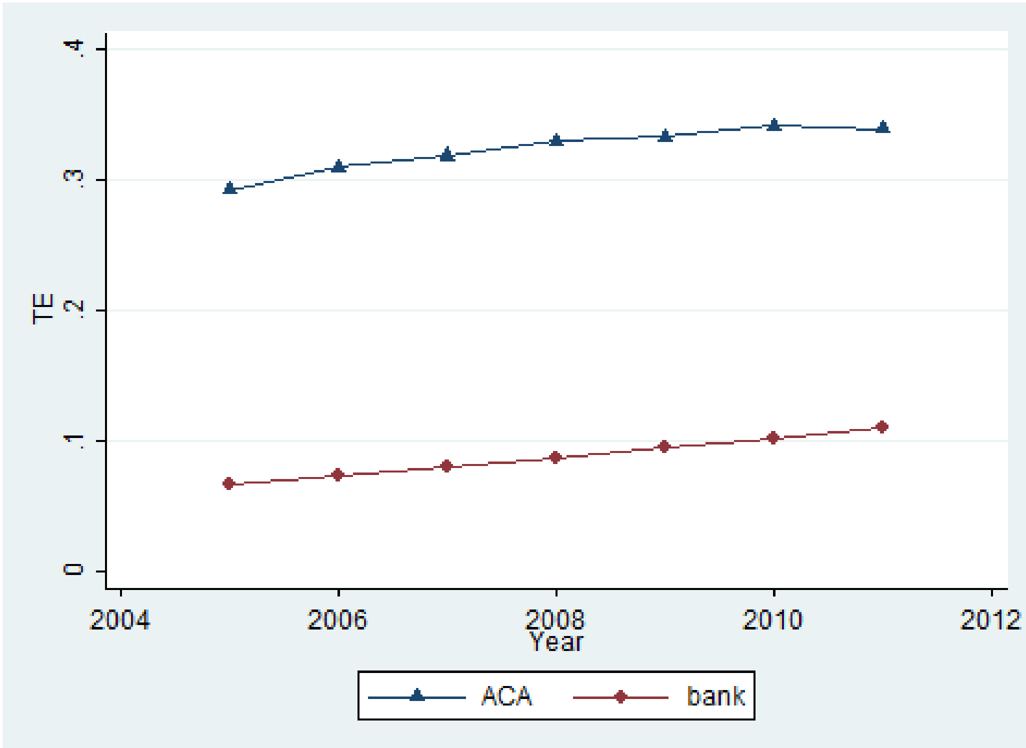


Figure 3.2: Trends in Technical Efficiency Levels, by Lending Units Type, 2005-2011

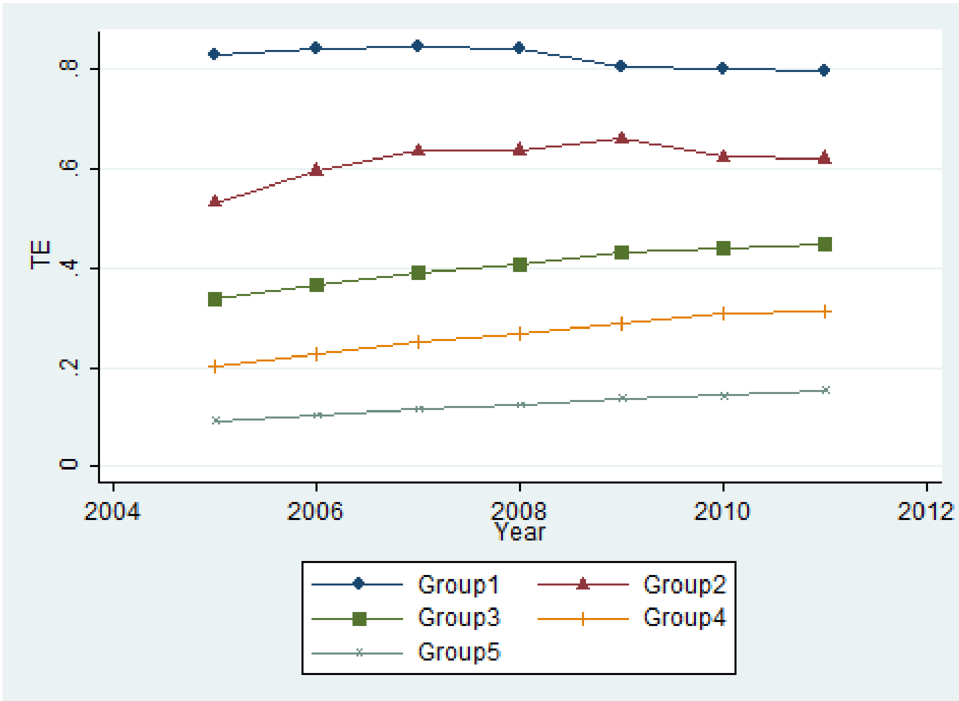


Figure 3.3: Trends in Technical Efficiency Levels, by Groups, 2005-2011

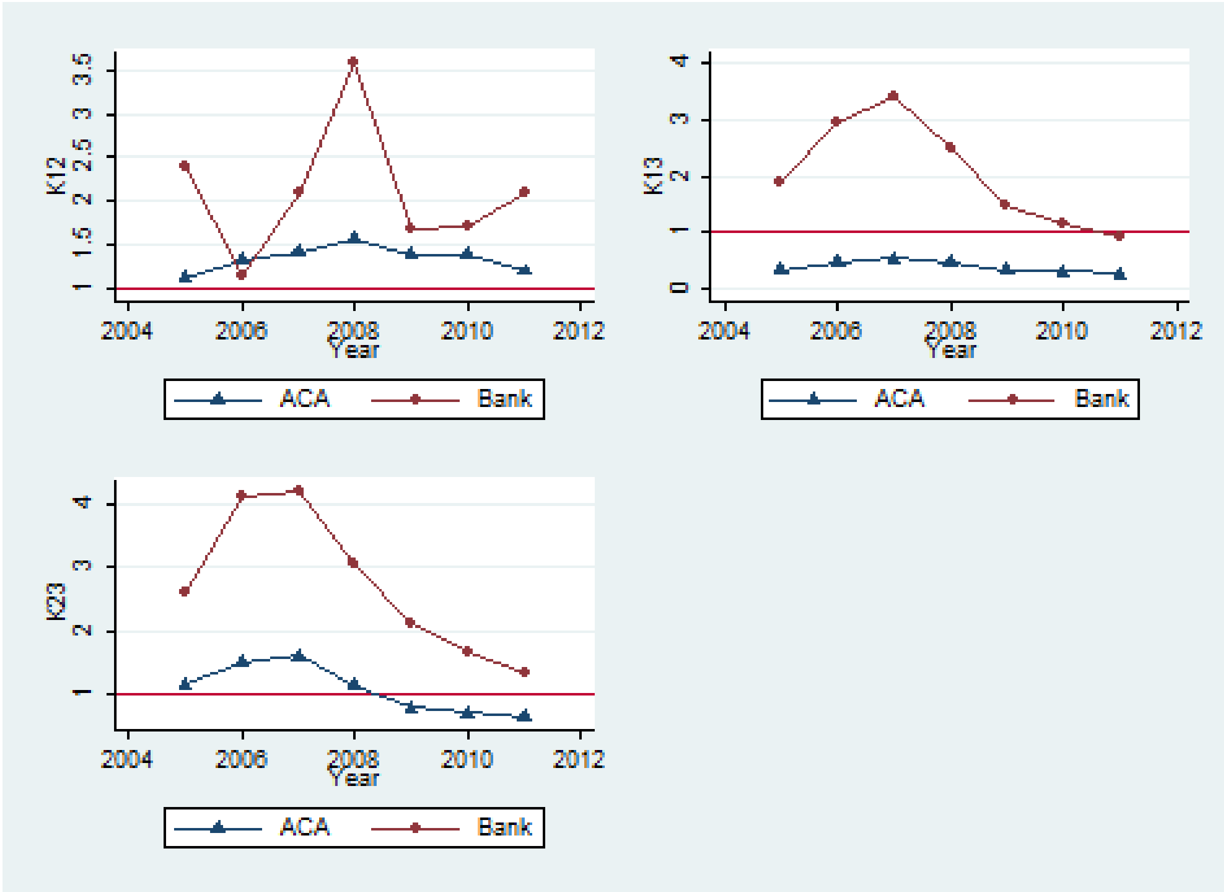


Figure 3.4: Plots of Input Allocation Ratios (k_{jh}) by Lending Units Category, 2005-2011

Figure 3.5: Plots of Input Allocation Ratios (k_{jh}), by Group Category, 2005-2011

CHAPTER 4

MAINTAINING BUSINESS VIABILITY THROUGH THE FINANCIAL AND NATURAL ADVERSITIES OF THE LATE 2000S: EVIDENCE FROM SOUTHEASTERN AND MIDWESTERN FARMS

4.1 Introduction

Farmers in the United States faced the daunting task of keeping their businesses afloat and viable during the late 2000s. The challenges that farm businesses faced came from two fronts. At the financial front, the 2007-2008 financial crises hit the global financial market so badly that in response to the surge of business bankruptcies, credit providers resorted to some restrictive lending policies designed to protect their wealth positions and maintain viable operations to survive the crises. Among these restrictive remedies was the tightening of credit conditions that led to strict screening of borrowing clients where only the more credit worthy borrowers end up being accommodated. As agriculture is a capital or investment intensive business, farmers found it hard to obtain credit from financial institutions to operate and survive through the period of financial crisis.

As though the financial difficulties from the economic crises were not enough, nature also unleashed its own barrage of problems for farmers. Certain regions in the country had to contend with severe drought conditions through the 2000s as the frequency and amount of precipitation fell to dismal levels that brought adverse effects to farms in the Southeastern and Midwestern regions. For example, dry conditions predominated during much of the year 2007 across large parts of the Southeast, West, and Upper Great Lakes (National Climatic Data Center). The droughts posed a threat of reducing crop yields significantly. The 2007 major field crops loss caused by the Southeastern drought has been estimated to be more than $1.3 billion (Manuel, 2008). During the same period, farmers faced declining agricultural commodity prices. The food and beverage commodity index (Figure 4.1) published by Mundi Index provides such indication as there was a significant drop in the index in 2008 and 2009. The reduction in both crops yields and selling prices could reduce farmers' income and significantly reduce their chances of business survival through such period of economic instability and difficulty.

This study will analyze the predicament of farmers in dealing with the difficult task of maintaining the viability and survival of their businesses during the financial and natural hardships of the late 2000s. A special focus of this study is the comparative analysis of financial and temporal endurance of farms differentiated by their geographical locations, farming activities, degree of specialization and size of farming operations. By looking at specifically farms that operate in the Southeastern and Midwestern regions, such differences in operating structures and environments will shed light on differentiated business survival or coping strategies.

A secondary feature of this study is its focus on farm borrowers who have been accommodated under the lending programs of the Farm Service Agency (FSA). The FSA provides loans to less creditworthy farmers who may experience difficulty to gain access to borrowing funds through the regular channels in the commercial credit market. FSA classifies its borrowers as "Commercial", "Standard", "Acceptable", and "Marginal" according to their credit quality. FSA implements two loan programs, the direct and guarantee loan programs, representing two mechanisms to help borrowers attain financial independence. The direct loan program provides direct loans to borrowers with farm ownership, operating, emergency and youth loans as main types of loans. Under the FSA guaranteed loan program, farmers borrow from commercial lenders and FSA guarantees loans by providing lenders with a guarantee of up to 95% of any eventual loss or borrowers' default on expected principal and interest payments on their loan obligation. The FSA guarantee loan program helps commercial lenders to provide credit to borrowers, who are not qualified under normal commercial loan approval criteria.

Using the FSA loaning accounting data together with other macroeconomic and national weather data, we can track a farm borrower's survival path during the periods of financial and natural adversities. Incidences of business failures are deduced from the farm borrowers' loan repayment records where serious delinquencies on loan payment obligations are regarded as indicators of failures. It is important to discern the nature of circumstances or farm conditions that will significantly influence the probability of farmers' survival and determine whether such capability and tendency to survive can be attributed to difference in regional resource endowments, farming activities, and business structures.

4.2 Data and Variables

This study utilizes quarterly borrower-level loan accounting data from the FSA national office from 2005 to 2010. Access to such protected 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 FSA collects the financial information of each existing borrowing client with outstanding loans on a quarterly basis. This study focuses on the time periods from the first quarter of 2005 to the fourth quarter of 2010, which is in total of 24 quarters. The sample time period covers the time before and after the 2007-2008 financial recession. Using the loan data, a specific loan account is classified as a loan default when its loan obligations have been unpaid past due for more than 90 days. Each borrower had been observed from first quarter of 2005 until the loan was defaulted or right censored. A loan account is considered to be right censored if it is paid without default or did not default by the fourth quarter of year 2010, which is the last quarter in our dataset.

In this study, the dataset compiled includes loan type information, such as operating loan, emergency loan, or farm ownership loan, as well as the borrower's demographic information, such as gender. The data set also includes borrower FSA classification codes for different risk classes. FSA class one is "Commercial" and is the highest rate. FSA class two is "Standard", FSA class three is "Acceptable", FSA class four is "Marginal", and FSA class five is "Not classified". The dataset is separated into two strata according to two different regions. One stratum is from the Midwestern region that includes the states of Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin. The other stratum is from the Southeastern region that includes the states of Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, and South Carolina.

Macro-economic data, such as a food and beverage commodity index and inflation data, are also collected. A quarterly drought index is also constructed for each county in the Southeastern and Midwestern regions. We first create a variable called negative rainfall difference. For each county, it is zero if the quarterly rainfall amount is greater than the mean quarterly rainfall. If the quarterly rainfall amount is less than the mean quarterly rainfall, the negative rainfall difference is the difference between the quarterly rainfall amount and the mean. The drought index in a particular county is the absolute value of the negative rainfall difference divided by the standard deviation of quarterly rainfall amount.

Summary statistics for the duration variable t, indicator for default or not, and other variables are shown in table 4.1. On average, the loans in Midwestern region have a longer duration or survival time and lower default rate than the loans in the Southeastern region. Principal of the loans from Midwestern region are larger than those in the Southeastern region. The Southeastern region' data reflect more loans for young farmers and have more operating types of loans. The Midwestern regions' data reflect fewer loans for young farmers and have more farm ownership types of loans. Borrowers in the Midwestern region on average have a higher Farm Service Agency credit rating than borrowers in the Southeastern region. Overall, the drought conditions seem more severe in the Southeastern region than in the Midwestern region.

4.3 The Analytic Framework

Assume there is a population of N borrowers, who may default the loan over time period (0, t) with the probability distribution function:

$$F(t) = \int_0^T f(t)dt \tag{1}$$

where f(t) is the associated probability density function and t is the duration between t=0 and the subsequent failure quarter T. The survival function is the probability of observing a surviving time (borrower does not default) greater than t, denoted as

$$S(t) = 1 - F(t) \tag{2}$$

The non-parametric Kaplan-Meier estimator of the survival function at time t is:

$$S^{\wedge}(t) = \prod_{t_{(i)} \leq t} \frac{n_{i-} d_i}{n_i} \tag{3}$$

where n_i is the number at risk of defaulting at time t_i and d_i *is* the observed number of defaulting.

The term "hazard" is used to describe the risk of "failure" in an interval after time t, conditional on the subject having survived to time t. The hazard function is:

$$h(t) = \frac{f(t)}{s(t)} \tag{4}$$

The cumulative hazard function is:

$$H(t) = \int_0^t h(u)dt = -\ln(s(t)) \tag{5}$$

The Split Population Survival Model

Many recent studies (Deng et al., 1997) on loan default use the Cox proportional hazards model, which has the benefit of not making strong assumptions on distributions of the parametric survival functions. However, the Cox proportional hazards model has a potential shortcoming assuming that all borrowers eventually default. So, it cannot identify the differences between the factors influencing failure and timing of failure (Cole and Gunther, 1994). If the population of borrowers split between borrowers that eventually default and borrowers that do not default, default and timing of default may depend on different factors.

We use the split population survival model (Schmidt and Witte, 1989) to examine jointly both the loan default and the timing of the default. Let D equal one for borrowers who eventually default on the loan, and zero for borrowers who do not default.

$$P(D = 1) = \delta, P(D = 0) = 1 - \delta. \tag{6}$$

We assume $F(t|D=1)$ to be the cumulative distribution function and $f(t|D=1)$ to be the density function for the borrowers who would eventually default. Let T be the duration of the follow up period, and let C be the observable dummy variable indicating whether the borrower defaulted by the end of the follow up period. We observe C=1 and the default time t, and the density is

$$P(D=1)f(t|D=1) = \delta f(t|D=1). \tag{7}$$

We only observe C=0 for non-default borrowers and the probability is

$$\begin{aligned} P(C=0) &= P(D=0) + P(D=1)P(t>T|D=1) \\ &= 1-\delta+\delta[1-F(T|D=1)] \\ &= 1-\delta+\delta S(t) \end{aligned} \tag{8}$$

We assume the distribution of time until default given the condition of default is log-logistic distribution. It has a relative flexible form that has a hazard function not monotonic and not constant in t with up to two inflection points. It can be a good fit if we expect the hazard may increase during the financial crisis period and then decrease afterwards. The log-logistic has the following survival and hazard functions:

$$S(t) = \frac{1}{1+(\lambda t)^p} \tag{9}$$

$$h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^p} \tag{10}$$

The likelihood function is:

$$L = \prod_{i=1}^{N}[\delta_i f(t_i|p,\lambda)]^{Q_i}\,[(1-\delta_i)+\delta_i S(t_i|p,\lambda)]^{1-Q_i} \tag{11}$$

where $Q_i = 1$ if borrower *i* defaults during the sample period (uncensored observations) and $Q_i = 0$ if borrower *i* does not default during the sample period or the loan is paid off (censored observations). The probability of default δ and the cross-sectional parameter λ can be made borrower specific as follows:

$$\delta_i = 1/[1 + e^{X_i\alpha}]. \quad (12)$$

$$\lambda_i = e^{-X_i\beta} \quad (13)$$

where X_i is a vector of borrower specific and other covariates, and parameter vectors α and β are to be estimated. The estimated α's measure the impact of the covariates on the probability that a borrower will not default. A positive α indicates that the covariate is associated with a higher probability of survival. The estimated β's measure the impact of covariates on a borrower's loan duration, given that a borrower will eventually default. A positive β indicates that the covariate is associated with a longer duration. We have $X_i\alpha = \alpha_1 * LP_i + \alpha_2 * DS_i + \alpha_3 * WTH + \alpha_4 * MAC$ and $X_i\beta = \beta_1 * LP_i + \beta_2 * DS_i + \beta_3 * WTH + \beta_4 * MAC.$ $The\ LP_i$ are loan related variables of each borrower, DS_i are demographic and structural variables, WTH are weather-related variables, and MAC are macroeconomic variables.

By substituting equations (9), (10), (12), and (13) into the likelihood function (equation (11)) and maximizing the log-likelihood function, the coefficients vectors α and β can be estimated. The model has a very flexible specification as the shape of the hazard function and the probability of survival, and the duration of the failure can vary from borrower to borrower.

4.4 Estimation Results

This study's dataset consists of farm businesses that incurred loans from the Farm Service Agency after 2005. These farms' financial information collected by the FSA from 2005 to 2010 will be used in this analysis, with the farm observations limited to the Southeastern and Midwestern region for purposes of comparison of regional differences in survival strategies. This study's time period captures the economic and natural conditions prior to the onset and after the late 2000s recession and the intermittent drought conditions that affected such regions at different times of the study period.

The non-parametric Kaplan-Meier estimates of the survival functions and hazard functions are calculated in order to determine any difference between the model results from Southeastern and Midwestern regions. Dividing data into two region strata, we plot the estimated survival functions in figure 4.2 and the cumulative hazard functions in figure 4.3. The plot of the survival functions shows that the borrowers in the Southeastern region are more likely to default than those in the Midwestern region. The log rank test's p value is less than 0.001, which shows that the survival functions of the two regions are different. The cumulative hazard curves also show that borrower in the Southeastern region are more likely to default. There are no significant changes in the hazards levels before, during, and after the recession.

This study's analytical model will allow for the scrutiny of both the farmer borrowers' probability of survival (at times referred to in this study as "financial endurance") and the length of time before each borrower succumbs to default (sometimes referred to here as "temporal endurance"). We would like to quantify farmer borrowers' probability of survival and time to default. Standard survival-time models, such as the proportional hazard model or other parametric models, do not consider a split population for default borrowers and non-default borrowers. Those models have potential severe drawbacks that assume all borrowers will eventually default. Thus, they cannot distinguish the differences between the factors that influence the probability of loan default and factors that may impact the timing of default. We can separate the population of borrowers into two groups: one group consists of borrowers who eventually default on the loan and the other group of borrowers who do not default on their loan obligations. Using the split population survival model, we can examine different factors that impact both loan default and timing of default.

Table 4.2 shows the results of the split population survival model for borrowers in Southeastern and Midwestern regions. Consistent with the Kaplan-Meier estimate of the survival functions, the estimated probability of default is higher in the Southeastern region than in the Midwestern region. The estimated probability of default for the average borrower in the Southeastern region is about 26.4% compared to about 24.1% in the Midwestern region. The temporal distribution of default is different between the two regions. Using the split population survival model in table 4.2, the estimated time for the first 25% of the borrowers who eventually defaulted is 13.58 quarters for Southeastern region and 14.26 quarters for Midwestern region. The estimated time for 50% of those borrowers who eventually defaulted is 31.72 quarters for Southeastern region and 29.41 quarters for Midwestern region.

We plot the estimated hazard functions for borrowers in both the Southeastern and Midwestern regions in figure 4.4. The log-logistic hazard functions are constructed by equation 10 for the estimated values of λ, p, and β with the mean values of covariates X for each region. Before eighth quarter, which is the beginning of year 2007, the hazards in the Southeastern region are higher than those in the Midwestern region. From year 2007, which is over the periods of financial crisis, the hazards in the Midwestern region are higher than those in the Southeastern region. The hazards of borrowers in both the Southeastern and Midwestern regions peaked in the financial crisis periods and went down after the financial crisis.

Determinants of the Probability of Survival

As discussed in this study's analytic model, the covariates associated with α measure their impact on the probability that a borrower will not default. A positive coefficient indicates a higher probability of survival, or conversely a lower probability of default.

For the borrowers in Southeastern region, the coefficients of the probability of survival are shown in Panel A part 1 of table 4.2. The farm ownership type of loans and FSA rating levels of 1 and 2 ("Commercial" and "Standard" rating) contribute positively and significantly to the probability of survival (non-defaulting). The total amount of loan, young borrowers, operational type of loans, the price of commodities, and the severity of drought contributes negatively and significantly to the probability of survival (non-defaulting).

For the borrowers in Midwestern region, the coefficients of the probability of survival are shown in Panel B part 1 of table 4.2. The farm ownership type of loans and FSA rating levels of 1, 2, and 3 ("Commercial", "Standard", and "Acceptable" rating) contribute positively and significantly to the probability of survival (non-defaulting). The total amount of loan, young borrowers, operational type of loans, the price of commodities, and the severity of drought contribute negatively and significantly to the probability of survival (non-defaulting).

In both Southeastern and Midwestern regions, higher FSA rating level will increase a borrower's probability of non-default on its loan obligation. The greater the principal of the loan, which is the amount owed, the greater probability the loan will be default. Young borrowers are more likely to default the loans. Operating loans seem to be more risky and more likely to default. The lower the price of agricultural commodities and the more severe the drought conditions are, these conditions will more likely cause a loan to default.

Determinants of Temporal Endurance

The split-population model offers the advantage of being able to separate the factors that influence the survival time from those that influence the probability of survival. This section analyzes the results for the coefficient vector β that measures the influence of covariates on the loan's survival time. The temporal endurance analysis focus on how certain factors can either expedite a borrower's retrogression into default 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 default.

For the borrowers in Southeastern region, the coefficients of the survival time are shown in Panel A part 2 of table 4.2. The young borrowers, farm ownership type of loans, operational type of loans, and FSA rating levels of 1 and 2 ("Commercial" and "Standard" rating) contribute positively and significantly to the survival time (non-defaulting). The total amount of loan, the price of commodities, and the time periods of financial crisis negatively and significantly affect the survival time (non-defaulting).

For the borrowers in Midwestern region, the coefficients of the survival time are shown in Panel B part 2 of table 4.2. The young borrowers, farm ownership type of loans, operating loan accommodations, and FSA rating levels of 1, 2, and 3 ("Commercial", "Standard", and "Acceptable" rating) contribute positively and significantly to the survival time (non-defaulting). The total amount of loan, the price of commodities, the severity of drought, and the time periods of financial crisis contribute negatively and significantly to the survival time (non-defaulting).

In both Southeastern and Midwestern regions, a higher FSA rating level will extend a borrower's survival time. The greater the principal of the loan, which is the amount owed, the shorter the duration of the loan. The lower price of agricultural commodities will also reduce a borrower's survival time. The period of financial crisis significantly reduces the duration of loans in the Southeastern region, although the effect is not that significant in the Midwestern region.

Comparisons of Coefficients between the Two Regions:

We compare the coefficients of probability of survival and survival time between the Southeastern and Midwestern regions in table 4.3. The Panel (A) – (B) shows the differences of the coefficients and the pooled standard deviations of the coefficients. For the determinants of the probability of survival, the difference of the coefficients of youth loan, operational type of loan, and drought index are significantly different. Both the youth loan and drought index in the Southeastern region contribute more negatively to the probability to survive than those in the Midwestern region. Operating loans in the Southeastern region contribute more positively to the probability of survival than those in the Midwestern region. For the determinants of the survival time, the difference of the coefficients of principal of loan, youth loan, and operating loan are significantly different. The youth loan in the Southeastern region contributes more positively to the time to survive than that in the Midwestern region. Both the principal of loan and operating loan accommodations in the Southeastern region contribute more negatively to the time to survive than those in the Midwestern region.

4.5 Summary and Conclusions

Farmers in the United States had to deal with the difficult challenge to overcome business obstacles arising from economic downturns and natural adversities in the late 2000s. In this study, we focus on the comparative analysis of financial and temporal endurance for farmers in the Southeastern and Midwestern regions. Compared to those in the Southeastern region, borrowers in the Midwestern region operate larger businesses, incurring larger loans, mostly farm ownership loans, and their overall productivity has been relatively less affected by drought conditions.

Using a quarterly FSA loan performance data from 2005 to 2010, a split-population duration model is used to evaluate the determinants of farmer loan survival and duration time. In contrast to the Cox proportional hazards model, the split-population model jointly identifies the differences between the factors impacting loan default and time of default.

The estimated hazard functions from the split-population model show that the hazard rates of Southeastern farmers were higher than those in the Midwestern region before the financial crisis. The hazard rates of Southeastern farms were lower than those in the Midwestern region after the financial crisis. On average, the probability of a loan default is higher in the Southeastern region than that in the Midwestern region. Also, on average the survival time of loan accommodations to Midwestern farm borrowers is longer than that in the Southeastern region.

For the determinants of the probability of survival, a higher FSA rating level will increase a borrower's probability of survival. A larger principal of the loan, young borrower, and operating loan will decrease a borrower's probability of survival. External shocks, such as lower prices of agricultural commodities and harsh weather conditions, will also decrease a borrower's probability of survival.

For the determinants of duration of survival, a higher FSA rating level will extend a borrower's survival time. A larger principal of the loan and lower price of agricultural commodities will reduce a borrower's survival time.

We compare the coefficients of probability of survival and duration of survival between the borrowers in the Southeastern and Midwestern regions. For the coefficients of the probability of survival, youth loan and severe weather contribute more negatively to the probability of survival in the Southeastern region than those in the Midwestern region. Operating loans contribute more positively to the probability of survival in the Southeastern region than those in the Midwestern region. For the coefficients of the duration of survival time, youth loan contributes more positively to the duration of survival in the Southeastern region than that in the Midwestern region. The principal of loans and operating loan accommodations contribute more negatively to the duration of survival in the Southeastern region than those in the Midwestern region.

The results of this study can be used to predict the probability of loan default and the duration of loans in different regions, as the Southeastern and Midwestern regions have different resource endowments and different farmer activities and business structures. This will help policy makers to implement different policies or loan help plans in different regions.

Table 4.1. Summary Statistics

		Southeastern		Midwestern	
Variable	Description	Mean	S.D.	Mean	S.D.
t	duration (quarters)	14.80	7.96	16.42	7.69
default	=1 if default and 0 otherwise	0.16	0.36	0.09	0.28
Prin	Unpaid principal amount ($)	31,206	52,056	58,245	66,598
Intrate	Interest rate on FSA loan	4.40	1.46	4.25	1.31
Youth	Indicator for Youth Loans: 1 = youth and 0 other wise	0.17	0.38	0.07	0.26
FO	Indicator for farm ownership loan : 1= FO and 0 otherwise	0.17	0.38	0.31	0.46
OL	Indicator for operating loan : 1= OL and 0 otherwise	0.73	0.45	0.60	0.49
FSA_1	FSA classification (Ranging 1 to 5): level 1 –"Commercial"	0.08	0.27	0.13	0.34
FSA_2	FSA classification (Ranging 1 to 5): level 2 – "Standard"	0.19	0.40	0.29	0.45
FSA_3	FSA classification (Ranging 1 to 5): level 3 – "Acceptable"	0.56	0.56	0.40	0.49
FSA_45	FSA classification (Ranging 1 to 5): level 4 – "Marginal" or level 5 – "Not Classified"	0.12	0.33	0.15	0.36
Gender	Indicator: 1= Male and 0 = Female	0.70	0.46	0.77	0.42
Commodity	Commodity Price index	138.07	27.51	143.29	26.86
Drought index	Standardized drought index	0.43	0.30	0.12	0.19

Table 4.2 Split-Population Model for Borrowers in the Southeastern and Midwestern Regions

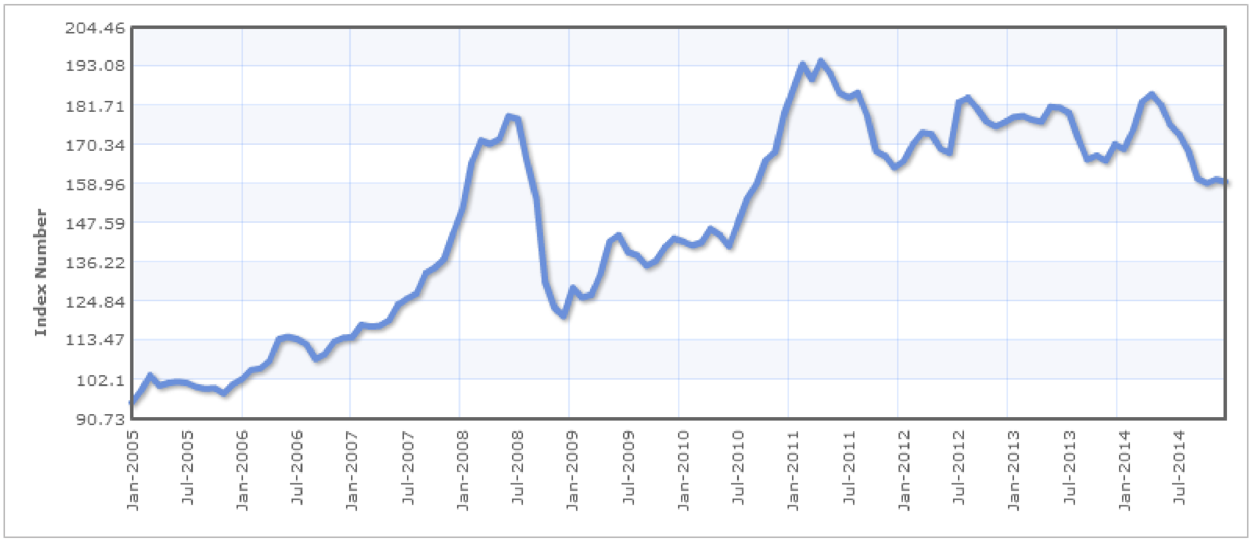
	(A) Southeastern Region		(B) Midwestern Region	
	Estimate	S.E.	Estimate	S.E.
λ	0.032	0.052	0.034	0.052
p	1.295 ***	0.019	1.517***	0.034
Log Likelihood	-23643.1		-15935.5	
(1) Probability of survival coefficient				
Constant	-0.942 **	0.394	0.448	0.431
Prin	-0.186 **	0.066	-0.0688	0.063
Intrate	1.6534	8.066	5.495	3.234
Youth	-9.752 ***	1.109	-1.887 ***	0.580
FO	0.6305 ***	0.210	1.0836 ***	0.154
OL	-4.058 ***	1.002	-12.054 ***	0.485
FSA_1	1.727 ***	0.253	1.534 ***	0.194
FSA_2	0.739 ***	0.141	0.836 ***	0.125
FSA_3	0.235 **	0.116	0.069 ***	0.103
Gender	0.168	0.136	0.021	0.122
Commodity	-3.254 ***	0.872	-2.864 ***	0.531
Drought index	-1.401 **	0.620	0.512	0.590
Rec_ind	0.322	1.160	-0.147	1.154
(2) Survival time coefficient				
Constant	4.782 ***	0.156	4.318 ***	0.208
Prin	-0.159 ***	0.021	-0.081 ***	0.021
Intrate	-31.600 ***	1.406	-34.053 ***	1.464
Youth	0.363 ***	0.046	0.104 *	0.059
FO	0.707 ***	0.185	0.533 ***	0.171
OL	1.090 ***	0.095	1.480 ***	0.135
FSA_1	0.545 ***	0.083	0.694 ***	0.079
FSA_2	0.321 ***	0.051	0.416 ***	0.049
FSA_3	-0.027	0.040	0.072 *	0.043
Gender	-0.105 ***	0.035	-0.088 **	0.040
Commodity	-0.606 ***	0.102	-0.406 ***	0.082
Drought index	0.097	0.061	-0.348	0.300
Rec_ind	-1.010 ***	0.193	-0.809 ***	0.133

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 4.3 Split-Population Model Coefficients Comparison for Borrowers in the Southeastern and Midwestern Regions

	(A) Southeastern Region Estimate	S.E.	(B) Midwestern Region Estimate	S.E.	(A) - (B) Difference	S.E.
(1) Probability of survival coefficient						
Constant	-0.942 **	0.394	0.448	0.431	-1.390**	0.594
Prin	-0.186 **	0.066	-0.0688	0.063	-0.117	0.099
Intrate	1.653	8.066	5.495	3.234	-3.842	12.153
Youth	-9.752 ***	1.109	-1.887 ***	0.580	-7.865***	1.670
FO	0.6305 ***	0.210	1.0836 ***	0.154	-0.453	0.316
OL	-4.058 ***	1.002	-12.054 ***	0.485	8.000***	1.510
FSA_1	1.727 ***	0.253	1.534 ***	0.194	0.193	0.382
FSA_2	0.739 ***	0.141	0.836 ***	0.125	-0.097	0.212
FSA_3	0.235 **	0.116	0.069 ***	0.103	0.166	0.175
Gender	0.168	0.136	0.021	0.122	0.147	0.204
Commodity	-3.254 ***	0.872	-2.864 ***	0.531	-0.390	1.314
Drought index	-1.401 **	0.620	0.512	0.590	-1.913***	0.934
Rec_ind	0.322	1.160	-0.147	1.154	0.469	1.747
(2) Survival time coefficient						
Constant	4.782 ***	0.156	4.318 ***	0.208	0.464**	0.235
Prin	-0.159 ***	0.021	-0.081 ***	0.021	-0.078**	0.032
Intrate	-31.600 ***	1.406	-34.053 ***	1.464	2.453	2.119
Youth	0.363 ***	0.046	0.104 *	0.059	0.259***	0.069
FO	0.707 ***	0.185	0.533 ***	0.171	0.174	0.278
OL	1.090 ***	0.095	1.480 ***	0.135	-0.390***	0.143
FSA_1	0.545 ***	0.083	0.694 ***	0.079	-0.149	0.125
FSA_2	0.321 ***	0.051	0.416 ***	0.049	-0.095	0.076
FSA_3	-0.027	0.040	0.072 *	0.043	-0.099	0.061
Gender	-0.105 ***	0.035	-0.088 **	0.040	-0.017	0.053
Commodity	-0.606 ***	0.102	-0.406 ***	0.082	-0.2	0.154
Drought index	0.097	0.061	-0.148	0.300	0.245	0.192
Rec_ind	-1.010 ***	0.193	-0.809 ***	0.133	-0.201	0.290

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.



Description: Commodity Food and Beverage Price Index, 2005 = 100, includes Food and Beverage Price Indices

Unit: Index Number

Source: International Monetary Fund

Figure 4.1 Commodity Foods and Beverage Price Index

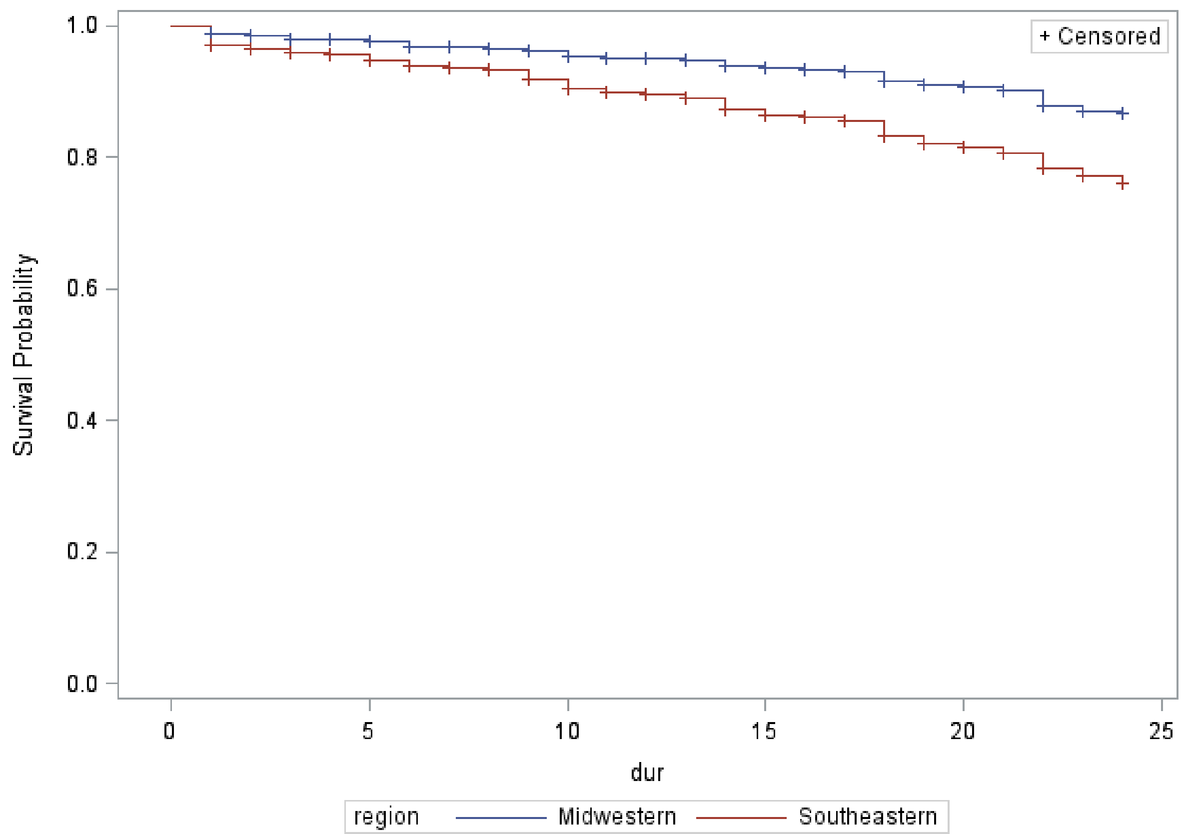


Figure 4.2 Survival Probabilities (Non Default) of Southeastern and Midwestern Regions

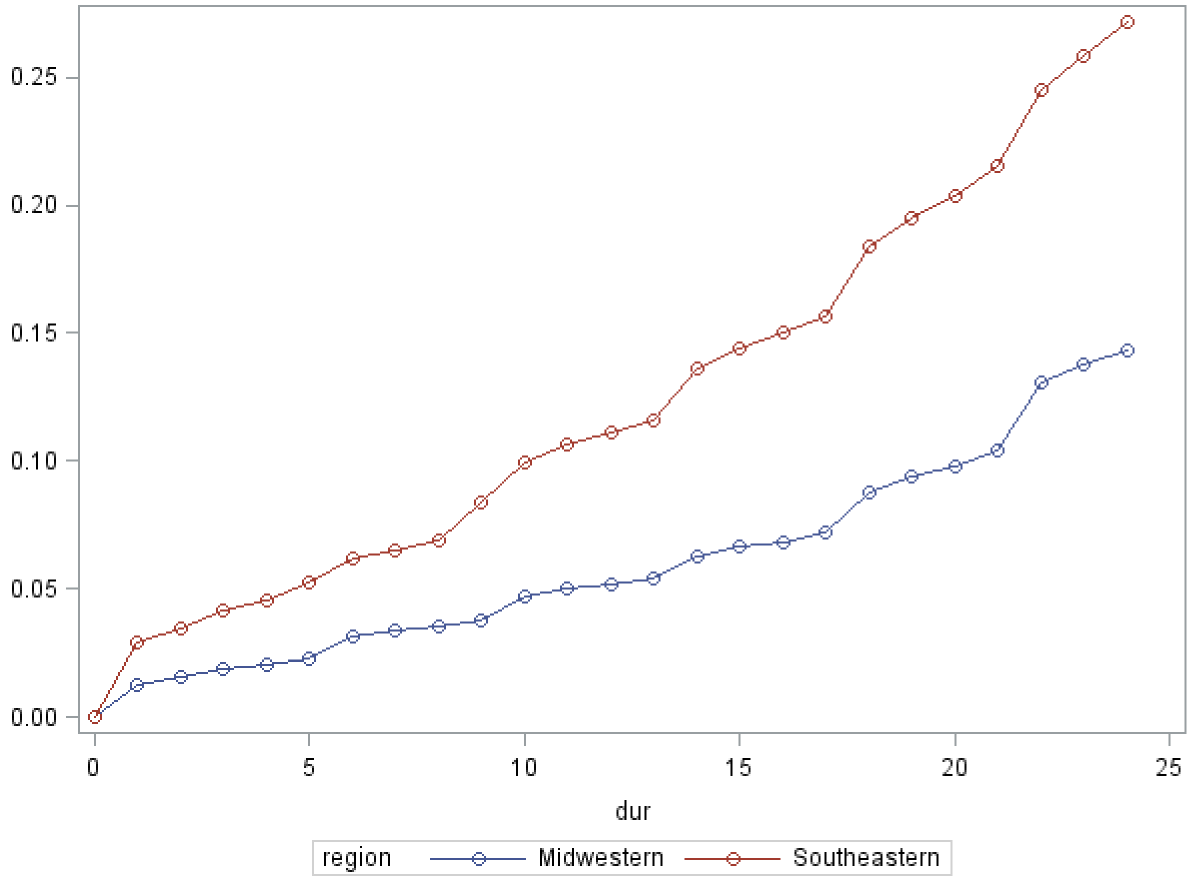


Figure 4.3 Cumulative Hazards of Southeastern and Midwestern Regions

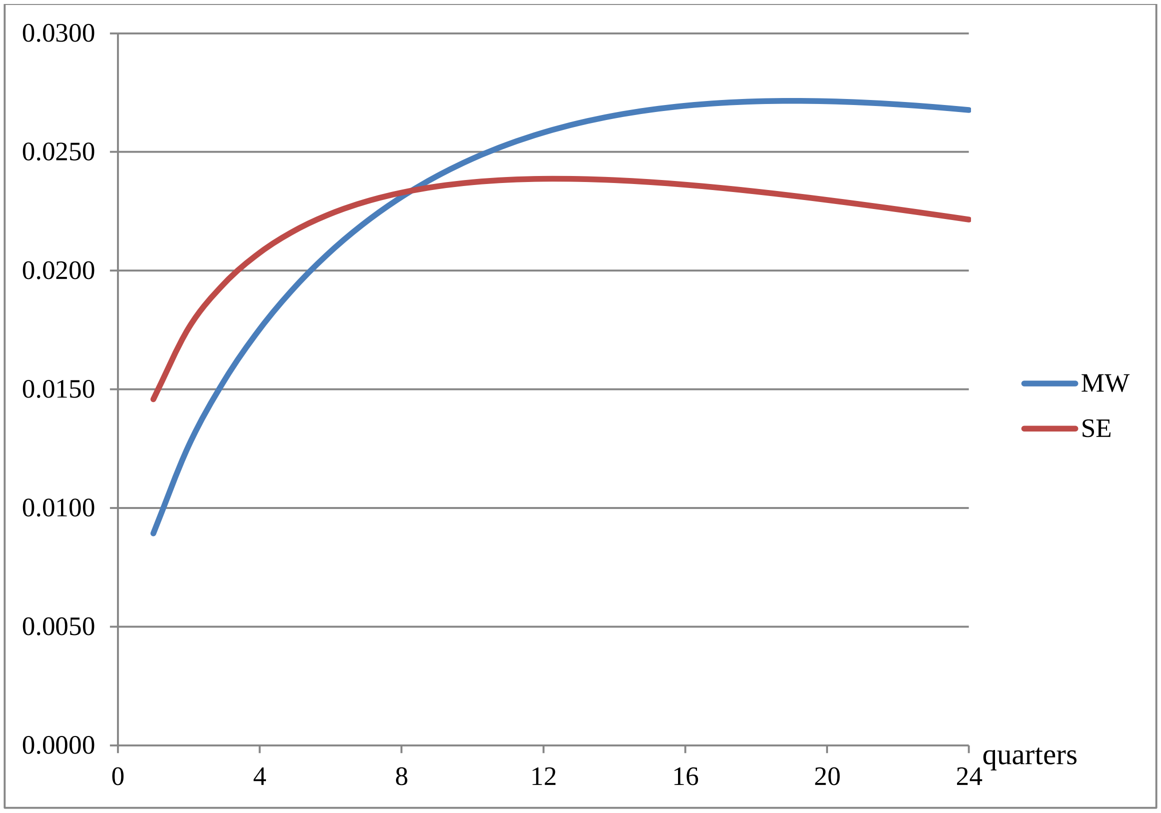


Figure 4.4 Estimated Hazards of Southeastern and Midwestern Regions from Split Population Survival Model

CHAPTER 5

SUMMARY AND CONCLUSIONS

5.1 Summary and Conclusion

The food production industry is exposed to risks from natural and economic shocks. As such, producers face the difficult challenge of managing such risks and maintain the viability of their business. This dissertation is comprised of three studies on the coordination mechanisms of producers and lenders responding to natural and economic hardships.

The first study focuses on the technology adoption of hybrid seeds from smallholder farmers in Kenya. Overall, easy access to market and improvements in extension services will improve the chances for a smallholder to adopt hybrid seeds and increase the quantities of the usage of the hybrid seeds. We also find that restrictions of credit and distance to the market are the main barriers to initial adopters. The availability of financial institutes and infrastructures are important in retaining and increasing the adoption of hybrid seeds. So, government in sub-Saharan African countries should increase the availability and quality of extension service, improve access to market, and provide credit for smallholders.

The second paper applied the stochastic Translog input distance function and stochastic frontier analysis (SFA) method to evaluate the operational efficiency if Farm Credit System (FCS) lending institutions before and after the 2007-2009 global and U.S. economic recessions. FCS is a government sponsored financial institutions to provide loans to farmers and is a major player other than commercial banks in the agricultural credit market. According to the FCS structure, the efficiency analysis is conducted on lending institutions classified based on type, such as banks and associations, and on asset size. The overall technical efficiency (TE) levels show that both FCS banks and credit associations operate below efficiency, although credit associations' TE is better than those of FCS banks. Among the size categories of the FCS lending institutions, smaller lenders tend to have relatively higher TE levels than larger lenders. For input allocation decisions, we study the relative input allocation decision ratios among labor, physical capital, and financial capital. For the input allocation ratio between labor and physical capital, it seems that FCS lending units over utilized physical assets while underutilizing their labor inputs. For labor vs. financial assets, it seems that banks over utilized their financial assets while credit associations over utilized their labor. For physical assets vs. financial assets, the results show that FCS banks over utilized financial assets and credit associations over utilized financial assets during the recession and over utilized physical assets after the recession.

The third paper focuses on the comparative analysis of financial and temporal endurance for farmers in the Southeastern and Midwestern. The split-population model is used to jointly identify the difference between the determinants of loan default and time of default. Estimated by the split-population model, the hazard rates estimated for the Southeastern region are higher before the financial crisis and lower after the financial crisis than those of the Midwestern region. On average, the survival time of the loan is longer in the Midwestern region than in the Southeastern region.

Higher FSA rating increases the probability that a loan will not default. A large principal of the loan, youth loan program, and operating loan, low price of agricultural commodities, and drought weather will increase the probability that a loan will default. Higher FSA rating will have a longer survival time of the loan. A larger principal of the loan and lower price of agricultural commodities will reduce the survival time of the loan.

5.2 Recommendation for future research

The first paper uses the survey data from year 1996 to year 2000. Various models use many independent variables covering housing demographics, production characteristics, cost factors, marketing activities, and public infrastructures. The econometric model can be improved further by accounting for some possible endogeneity issues among the independent variables through perhaps the use of instrument variables.

The second paper studies the technical efficiency and allocation efficiency of the Farm Credit System lending units. The performance of the FCS banks and credit associations is compared. The banking industry and the FCS, though rivals in farm lending, have altogether provided crucial financial assistance to farm businesses with synergistic impacts on the growth and expansion of the U.S. agricultural industry. We could extend the research to study the operation efficiency and strategic decisions between FCA lending units and commercial banks. The lending institutions' input allocation decisions will be analyzed and compared to find any difference in operating or management strategy for enduring the financial crisis.

The third paper focuses on the comparative analysis of financial and temporal endurance for farmers in the Southeastern and Midwestern regions. Using the split-population model, factors impacting both the default status and duration of the FSA loans are analyzed. The FSA has direct loan and guaranteed loan programs to help farmers with low credit ratings. Direct loan borrowers are expected to eventually transit to guaranteed loan or commercial loan. It is important to analyze how those borrowers performed during periods of economic and natural hardship. An analysis of movements in the quality of FSA's high risk direct loan borrowers would provide implications for operating and risk control strategies.

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