An examination of the resilience of Kansas farms

by

Michael Burnett Lindbloom

B.S., University of Illinois, 2008
M.S., Southern Illinois University, 2011

AN ABSTRACT OF A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agriculture Economics
College of Agriculture

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Manhattan, Kansas

2018

Abstract

The drop in average U.S. net farm income from 2014 through 2016 has indicated that current risk management options available to farmers have not fully mitigated the risks associated with farming. Although there are more risk management tools available to farmers today than there have been in the past, there is still a need to improve upon the available options and create new ways of securing agricultural production into the future. In an effort to improve how farmers cope with risk and uncertainty, system resilience concepts have started to find applications in production agricultural research. Agricultural resilience can generally be defined as the ability of an agricultural production system to return to normal (or improved) operations after having experienced an unexpected economic or environmental shock.

The contribution of this research was to conduct an empirical analysis of farm resilience based on existing theories in system and agricultural resilience. A conceptual model was developed to apply an existing resilience measure, the resilience triangle, to a production agriculture setting and a model of farm resilience was constructed based on the existing literature in agricultural resilience. In this model, farm resilience is driven by three defining capabilities: buffering capability, adaptive capability, and transformative capability.

The data for this analysis was obtained from the Kansas Farm Management Association (KFMA). Based on the literature review and the conceptual framework, resilience triangle areas were computed for individual farms during two distinct periods of economic shock, 1980 and 1998. An index of farm resilience was generated from the resilience triangle areas, which were then used as dependent variables in the econometric analysis. A fractional response logit model was estimated to test hypotheses about the impact of the different resilience capabilities on overall resilience index values. The results of the analysis indicated that there are differences in

the ways that buffering and adaptive capabilities impact overall farm resilience, however there were not conclusive findings that buffering capabilities were stronger among the resilient farms as compared to the non-resilient farms. These results indicate that farm resilience is driven by both buffering and adaptive capabilities jointly. Even though buffering capabilities are important at the outset of a shock, the farm will then need adaptive capabilities to recover from the initial impact of the shock.

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Table of Contents

List of Figures

List of Tables

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In addition, I thank Dr. Vincent Amanor-Boadu for spending many hours in conversation to help craft and sharpen my theoretical and empirical thinking. Also, I offer many thanks to Dr. Terry Griffin. Dr. Griffin provided me with invaluable advice on scientific writing and I am sincerely grateful for the significant amount of time he has spent editing my writing.

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Dedication

I dedicate this work first and foremost to my parents, Robert and Synthia Lindbloom. You knew me before I knew myself. You were the ones that stayed awake through the nights when I was new to the world. You were the ones that first helped me to explore this big world. You were the ones who taught me the values of hard work, dedication, and patience. You were the ones who taught me to have an open mind and a loving heart. For all that I am, and all that you have done for me, thank you.

I also dedicate this dissertation to my sons, Sebastian and Aydin. The two of you have already taught me more than you will ever know, and I hope that forever and ever you both shine as brightly as you do now.

Chapter 1 – Introduction

1.1 Statement of the Problem to be Investigated

During the three-year period from 2014 through 2016, average U.S. net farm income declined by approximately 56 percent (Featherstone, 2016). This large drop in net farm income was not experienced equally across all regions of the U.S., but data from the Kansas Farm Management Association (KFMA) has shown that most regions of Kansas experienced a similar drop in net farm income during that time period. Although fluctuations in net farm income have not been uncommon over time, as shown in Figure 1.1, this recent plunge in average farm profitability was one of the most severe drops since the 1980's farm crisis. This indicates that the current set of risk management options available to farmers cannot entirely protect them from large drops in net farm income. Therefore, improvements can be made to the risk management tools available to farmers in order to better protect them from future shocks.

In an effort to improve how farmers cope with risk and uncertainty, system resilience concepts have started to find applications in production agricultural research. Agricultural resilience can generally be defined as the ability of an agricultural production system to return to normal (or improved) operations after having experienced an unexpected economic or environmental shock. This definition is based on the existing body of literature concerned with agricultural resilience (Berardi et al., 2011; Lin, 2011; Hammond et al., 2013; Milestad et al., 2012), as well as the broader concepts of system resilience (Bhamra et al., 2011; Brand and Jax, 2007; Carlson et al., 2012; Martin-Breen and Anderies, 2011) and ecological resilience (Carpenter et al., 2001; Folke et al., 2004; Folke, 2006; Holling, 1973). Broadly speaking, system resilience embraces the fact that every productive system will always be subject to some level of unpreventable vulnerability (Juttner & Maklan, 2011), thereby demanding that the system either endure or adapt for survival.

1.2 Objectives

The methods that were employed for this research were driven by two broad objectives. The first objective was to establish and compute an index of farm resilience. The second objective was to classify, measure, and compare resilience-enhancing capabilities of farms after they have experience some kind of economic shock.

The first objective was achieved by adapting the “Resilience Triangle” approach first proposed by Bruneau et al., (2003). This method has since been explored and developed in a variety of settings (Sheffi and Rice, 2005; Bruneau and Reinhorn, 2007; and Tierney and Bruneau, 2007; Falasca et al., 2008, Cimellaro et al., 2010; Zobel, 2010; Zobel, 2011; Pant et al., 2014; Carvalho et al., 2011; Guller et al., 2015). With the resilience triangle approach, the extent of a system’s resilience is defined by the area of the triangle that results from connecting three points on a graph: (a) pre-shock performance level, (b) minimum post-shock performance level, and (c) post-recovery performance level. Intuitively, systems with large resilience triangles will have lower levels of resilience (large impact of the shock, long recovery, or both), and systems with smaller resilience triangles will have greater resilience (smaller impact of the shock, shorter recovery, or both). This method for measuring system resilience is comprehensive because it simultaneously measures both the impact of the shock as well as the time to recovery. Based on the existing literature, this method of measuring resilience follows the engineering approach to resilience as defined in Holling (1973). In this context, resilience is a concept that combines both the ability of the system to resist the shock (persistence) as well as the ability of the system to return to average or improved operations post-shock (duration). The resilience triangle combines both of these impacts into a single measure.

In order to make the resilience triangle areas easier to interpret, a resilience index was computed by taking the inverse of the resilience triangle area described above. In this way, higher values of the resilience index corresponded with more resilient farms. Resilience index values were computed at the farm level, the regional level, and the state level. The data used to compute the resilience index values was obtained from the Kansas Farm Management Association (KFMA). In total there were 879 observations used for this study, spanning two periods of statewide economic shock. For this study an observation was considered a single farm in one shock period. Therefore, a single farm could account for two observations if it was in operation and reporting to the KFMA in both shock periods. The full conceptual framework developed for the resilience triangle application to agriculture is presented in Chapter 3 (Sections 3.2 to 3.4) and the data are discussed in-depth in Chapter 4.

The second objective was to identify resilience-enhancing capabilities of farms and measure their impacts on overall farm resilience. Overall, three capabilities of farm resilience were selected based on Darnhofer (2014): (1) buffering capability, (2) adaptive capability, and (3) transformative capability. According to Darnhofer (2014), a farm's buffer capability is the capacity to withstand the impact of a shock (persistence). Adaptive capability "…requires resourcefulness, i.e. 'the ability to identify problems, establish priorities, mobilize resources in face of disruption, to combine experience and knowledge so as to adjust responses to a changing context or to changing preferences by family members.'" (Darnhofer, 2014). Finally, transformative capability is "…the ability to implement radical changes, the ability to create untried beginnings from which to evolve a new way of living." Using the resilience index value as the dependent variable and the three latent variables, the conceptual model is specified as:

$$R_i = f([B_i],[A_i],[\,T_i],[X_i]) \qquad (1)$$

where R_i is the resilience index value of farm_i, $[B_i]$ is a vector of variables representing the farm's buffering capability, $[A_i]$ is a vector of the farm's adaptive capability variables, $[T_i]$ is a vector of the farm's transformative capabilities, and $[X_i]$ is a vector of other farm-specific characteristics that impact resilience. For this study a fractional logit model was used based on the fact that R_i ranges between zero and one. The fractional logit regression was developed in Papke and Wooldridge (1996) to model employee participation rates in employer-sponsored 401(k) retirement plans. Since then, this type of regression has been used in a number of settings for which the dependent variable ranges between zero and one. This type of regression model was used because, as shown in Chapter 5, the resilience index values R_i ranged between zero and one.

1.3 Dissertation Outline

The remainder of this dissertation is structured as follows. Chapter 2 is a literature review of resilience concepts broadly, as well as, a review of the literature specific to agricultural resilience. In Chapter 3, the conceptual framework is developed, which is structured into four parts. The first part, section 3.1, formally discusses the resilience triangle approach. Next, section 3.2 discusses the application of the resilience triangle to production agriculture. Section 3.3 presents the conceptual model of resilience. Finally, section 3.4 presents the hypotheses.

Chapter 4 discusses the data and the summary statistics. Chapter 5 presents the analysis, for which there are three parts. Section 5.1 discusses how values of the dependent variable for the econometric model were computed. Section 5.2 introduces the econometric model. Section 5.3 discusses how the independent variables were selected. Chapter 6 contains three sections. Section 6.1 discusses the results from computing the resilience index values, section 6.2 discusses the results from computing the resilience capabilities variables, and section 6.3 discusses the results from the econometric estimations. Finally, Chapter 7 offers a conclusion and discussion of the implications of this research.

Chapter 2 – Literature Review

2.1 Resilience Research

Resilience is a concept originating from ecology and psychology and has been increasingly applied in the fields of supply chain management, disaster response management, business management, and economics. Although a single, commonly accepted definition of resilience does not permeate all of these research disciplines, in its most basic sense resilience is the ability to withstand and recover from shocks. Holling (1996) posits that regardless of the discipline within which resilience concepts are being applied, the basic definition of resilience can be separated into two subsets. The first, which is called *engineering* resilience, "…concentrates on stability near an equilibrium steady state, where resistance to disturbance and speed of return to the equilibrium are used to measure the property." (Holling, 1996). In other words, engineering resilience refers to the ability of an individual or system to return to a previous state of equilibrium following the experience of a shock.

The second subset, called *ecological* resilience, measures resilience as "…the magnitude of disturbance that can be absorbed before the system changes its structure by changing the variables and processes that control behavior." (Holling, 1996). In other words, this means that the system does not necessarily return to a previous equilibrium steady-state after a shock, but can and will evolve over time into multiple equilibriums and steady states. In this definition of resilience, the fundamental structure of the system remains after the shock, even though parameters of the system may have changed.

To provide an example of engineering resilience, consider the ability of a steel beam to withstand physical pressure placed on it from some external force (weight for example). After applying some amount of pressure, the steel beam will begin to bend. After the pressure is removed the steel beam returns to its previously straight-line state of being (i.e. a return to the previous equilibrium). Consider also that if enough pressure is applied to the beam, it will eventually break. After this happens it would be impossible for the beam to return to its previous equilibrium state. The resilience of the beam, therefore, is the combination of beam's *resistance* to the pressure and the speed at which the beam returns to its straight-line equilibrium state after removing the pressure (Martin-Breen and Anderies, 2011). If the beam breaks, then it is not at all resilient. Moreover, if comparing two beams to each other reveals that one beam can withstand greater pressure and recover to its steady-state faster, then that beam is considered to be more resilient than the beam which recovers slower and can withstand only lesser amounts of pressure.

In contrast to engineering resilience, an entity can also be considered resilient even if it never returns to some pre-existing equilibrium steady state after a shock. An example often explored in the context of psychological resilience is when a child has had to endure a tragic life event (Werner, 1995; Rutter, 2006). The child could fail to recover properly and may end up in worse life situations following the tragedy. Alternatively, the child could recover, adapt, and go on to lead a happy and successful life. In either case, the child will never return to the state that he or she was in prior to the tragedy, but will fundamentally continue to grow and enter new states of being. In this context resilience is still measuring the ability to endure shock and then recover, however it would be impossible for the recovery to involve the child returning to some previous equilibrium state. Again, this kind of resilience is what Holling (1996) defines as ecological resilience. It is the capacity of the system (or individual) to experience a shock and still maintain its functions and controls, even if the system migrates or adapts to some new state (Carpenter et al., 2001; Gunderson and Holling, 2002).

A significant amount of research has emanated from the seminal ecosystem resilience work of Holling. Over time, this vein of research has sharpened the definitions and concepts of resilience. In particular, out of this progression came the adaptive cycle theory, or the theory of adaptive cycle management (Gunderson et al., 1995; Carpenter et al., 1999). Framing ecological resilience within this context posits that systems undergo periods of adaptation and evolution both before and after experiencing a shock. These adaptations and evolutions enable systems to better handle future shocks, and without them the system will eventually cease to exist. This extends the definition of resilience to not only include resistance and recovery, but also incorporates the ability of the system to reorganize in response to a crisis. From Carpenter et al. (2001), "According to the theory of the adaptive cycle, dynamical systems such as ecosystems, societies, corporations, economies, nations, and SES (social-ecological-systems) do not tend toward some stable or equilibrium condition. Instead, they pass through the following four characteristic phases; rapid growth and exploitation (r), conservation (K), collapse or release ("creative destruction", or Ω), and renewal or reorganization (α)." (Carpenter et al. 2001).

Whether the system is a Complex Adaptive System (CAS) (Levin, 1998; Walker et al., 2004) or a single mechanical structure (Martin-Breen and Anderies, 2011), an important consideration when assessing resilience is to first "…specify which system configuration and which disturbances are of interest." (Carpenter et al., 2001). From Carpenter et al., 2001:

> "Measurable, quantitative definitions of resilience would open new and important pathways for testable hypotheses related to the adaptive cycle. To interpret the dynamics of a particular system in terms of the adaptive cycle metaphor, so that we can try to understand the resilience of the system, we must begin by clearly defining resilience in terms *of* what *to* what. These aspects change depending on the temporal, social, and spatial scale at which the measurement is made. A socioecological system can be resilient at one time scale because of the

> technology it has adopted. Iron axes, for example probably helped emerging agricultural societies to persist over a particular span of time because they enabled their possessors to clear more forest and grow more food. But at a longer time scale, once some threshold of forest cover had been crossed, fallowing could no longer maintain soil fertility and the resilience of the system was compromised (Ruthenberg, 1976). In this example, resilience in one time period was gained at the expense of the succeeding period." (Carpenter et al., 2001)

In any study of resilience, therefore, two crucially important considerations are (1) establishing an appropriate time scale and (2) determining which components of the system are variables and which are parameters (Carpenter et al., 2001). Extending this notion to agricultural studies of resilience will mean selecting appropriate shock periods within which to conduct an analysis, as well as, identifying a suitable performance measure to use when measuring farm resilience.

2.2 Resilience Research in Agriculture

The existing body of agricultural resilience research has been largely driven by likening agricultural systems to social-ecological systems (SES's). There is a natural connection to be made between social-ecological systems and agricultural systems because agricultural systems inherently represent a coupling of human and natural systems (Carlisle, 2014). In particular, the adaptive cycle theories that have been established in the social-ecological resilience research have been integrated into studies of agricultural resilience. For example, Allison and Hobbs (2004) attempt to utilize the adaptive cycle theory (Holling, 1995) to measure the resilience of farms in the Western Agricultural Region. In another example Anderies et al. (2006) use adaptive cycle theories of social-ecological systems to examine the loss of resilience in intensive agricultural systems in southeastern Australia.

Continuing with this line of research, Darnhofer et al. (2010) and Milestad et al. (2012) propose that an agricultural system's capacity to adapt is a significant component of its ability to cope with rapid and unexpected change. These studies emphasize that although substantial economies of scale have driven massive increases in the productivity of modern agriculture, they have also diminished the ability of farms to quickly respond to external and internal shocks. In this way, resilience methods have been shown to have the capacity to improve the sustainability and resilience of farming systems.

Agricultural resilience research has also been concerned with identifying specific practices that could potentially improve resilience. For example, diversification is a management practice that can potentially lead to higher levels of farm resilience (Lin, 2011; Kremen & Miles, 2012). A diversified farm can withstand simultaneous disturbances to several crops on a regular basis, as well as promote and maintain viability and productivity (Featherstone and Moss, 1990; Purdy et al., 1997). "Enterprise diversification is particularly effective when the returns between two enterprises or groups of enterprises are uncorrelated or negatively correlated. Historically, many farms diversified their operations by producing both crops and livestock. By specializing, farms may be able to capture product-specific economies of size, but in the process may also reduce their ability to manage risk or capture economies scope." (Purdy et al., 1997).

Other farming management practices that have been proposed to improve resilience include a farmer's ability to live with change and uncertainty (i.e. adaptability), combining different types of knowledge and learning (experience), successful utilization of low-input production methods, crop rotation systems, propensity to self-organize, financial stability, and cooperation among rural community members (Darnhofer, 2010; Lin, 2011; Paronson-Ensor and Saunders, 2011; Kremen and Miles, 2012; Hammon et al., 2013; Carlisle, 2014). Changes in human, natural, social, cultural and physical capital have also been qualitatively and theoretically explored (Keil et al., 2007; Paronson-Ensor and Saunders, 2011), as well as the impact of agricultural policies on resilience (Berardi et al., 2011).

2.3 Contribution to the literature

The primary contribution of this research was to broaden and enhance the set of available risk management tools for agricultural production by using several of the concepts and methods that have originated in the system resilience literature. Although there have been major improvements in the ability of farmers to manage risk and uncertainty over the past several decades using things like crop insurance, drought-resistant crops, efficient irrigation systems, and sophisticated marketing channels, economic shocks have still resulted in negative impacts on net farm income. This is evidenced by the most recent 56 percent drop in net farm income mentioned above.

System resilience concepts have recently been applied in agricultural settings in an effort to strengthen farmers' resistance to economic shocks and improve the recoveries from these types of shocks. Resilience offers a new way of thinking about risk and uncertainty in agricultural because it is not focused on individual sources of risk, but instead seeks to cope with the general uncertainty that farmers face. The general philosophy of system resilience is to prepare for shocks by preparing to not only buffer the impact of shocks, but also by continually preparing to adapt in the face of change. Berardi, et al. (2011), posit that modern agriculture "…represents a cultural shift from adaptation to natural seasonal fluctuations in 'wild' food supply, to more intensive investment of labor and other resources for stability and predictability in caloric production via cultivation." However, seasonal fluctuations and the "wild" aspect of agricultural cannot be entire eliminated. So, rather than attempting to remove the fluctuations and instill absolute predictability in agricultural production, resilience thinking in agricultural production is about embracing the fact that there will be fluctuations and unpredictability, and then help to make farmers hardy in the face of shocks and flexible in the aftermath of shocks.

The developments that have been made in the existing literature concerned with agricultural resilience have generally been qualitative in nature. As a result, empirical applications of these theories are still relatively sparse. The diagram in Figure 2.1 shows that agricultural resilience research has stemmed primarily from the ecological definition of system resilience (Holling, 1996) and has been focused on framing agricultural systems within the socio-ecological adaptive cycle framework (Carlisle, 2014). Although analyzing farm resilience within a socio-ecological framework is intuitive and meaningful, this foundation may not fully capture the full picture of farm resilience. Farms are both socio-ecological systems as well as socio-economic systems. Farmers must indeed make tradeoffs between scarce resources in order to persist through time and their decisions are driven by many forces including profit, land stewardship, family sustainability, political motivations, ethical considerations, and community.

Based on the existing literature in both ecological system resilience and agricultural resilience, this study attempted to empirically measure farm resilience and quantify the impact of several resilience-enhancing capabilities. The results of this research will have impacts on producers, researchers, and policymakers. The existing risk management options that are available to agricultural producers are generally focused on creating automatic responses for individual types of shocks. For example, if there is a drought that results in a weak crop, then crop insurance will compensate for the loss. Or, if there is a drop in commodity prices as a result of oversupply on the market, then the automatic response is to collect government price support payments. Although not every producer will rely on every type of risk management option available, there still exists the philosophy of identifying sources of risk and then attempting to mitigate losses should these risks be actualized. The resilience approach, on the other hand, is focused on continually preparing farmers to face the inevitable risks in agricultural production. Resilience is focused on strengthening farmers' resistance to and ability to buffer against all types of environmental and economic shocks. In addition, it is simultaneously focused on ensuring that famers have formidable adaptive capabilities that promote speedy recovers and support the flexibility to respond to any number of post-shock scenarios. Finally, system resilience in agriculture is focused on bolstering the overall ability of a farmer to transform operations through time to accommodate the never-ending process of change that history has shown to be inevitable.

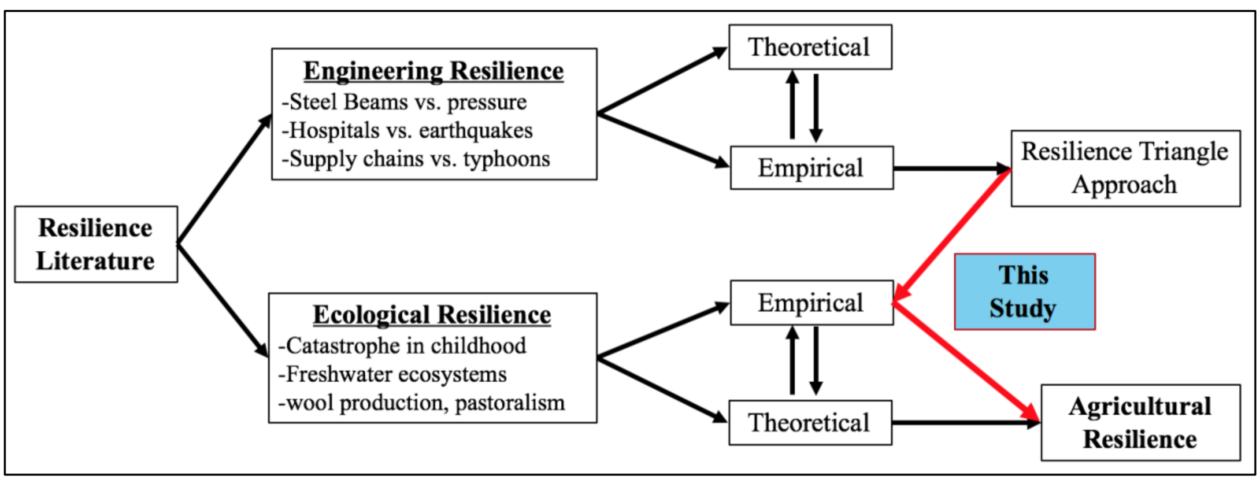

Figure 2.1: Diagram showing existing fields of resilience research and the contribution of this research to the existing body of literature

Chapter 3: Conceptual Framework

3.1 The Resilience Triangle Approach

The definition of agricultural resilience established in Chapter 1 is the ability of an agricultural production system to return to normal (or improved) operations after having experienced an unexpected economic or environmental shock. Based on this definition, a comprehensive measure of farm resilience must simultaneously incorporate both the impact of the shock, as well as, the length of time to recovery. Previous research has measured the abilities of farms to persist at particular levels of profitability, which has been called financial persistence (Langemeier, 2010; Herbel and Langemeier, 2012, Stabel et al., 2018). Resilience is different from persistence because it measures not just the ability of an agricultural production system to remain in a particular profitability category, but also incorporates the ability of the system to drop to lower categories and then recover to the original category. In this way, resilience is focused on the ability to resist a shock, but also to recover after the initial impact.

The resilience triangle approach is a method that has been developed to simultaneously measure both the impact of a shock, as well as, the time to recovery. This approach is rooted in the engineering definition of resilience analysis and a precursor to the resilience triangle was first proposed by Bruneau et al (2003) in an assessment of communities' resilience to earthquakes. This graphical approach (Figure 3.1) combines the two primary resilience components from the engineering standpoint: (1) magnitude of impact and (2) time to recovery. The level of resilience is measured by first graphing the quality of infrastructure at each point in time, from pre-shock to post-shock to post-recovery (if there is a recovery). Before a shock occurs, the quality of the infrastructure is at 100%. Then, at time t_0 there is a shock to the infrastructure and quality of the infrastructure drops to 50%. After time t_0, the relevant stakeholders begin the recovery process, which concludes at time t_1 when infrastructure quality has again reached the pre-shock level of 100%.

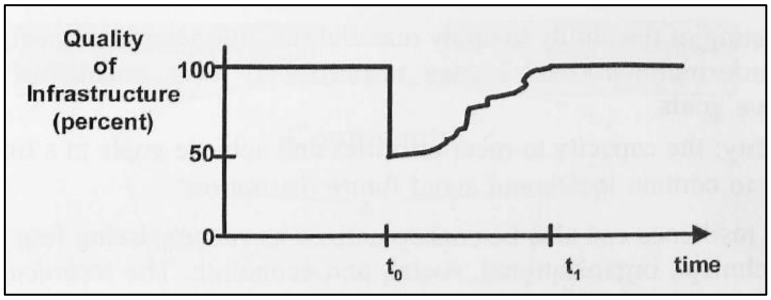

Figure 3.1: Precursor to Resilience Triangle (Bruneau et al., 2003)

Sheffi and Rice (2005) also proposed a predecessor to the resilience triangle called The Disruption Profile (Figure 3.2). This framework was generated within a discussion on how to improve the resilience of a business organization's supply chain that encounters some kind of disruption. It is a graphical representation of the stages that the organization will move through on the road to recovery. This is again an engineering approach to resilience because it is measuring the ability of a system to return to a previously established equilibrium.

As shown in Figure 3.2 (Sheffi and Rice, 2005), the level of performance of the supply chain is measured on the vertical axis and time on the horizontal axis. The time leading up to the disruption is defined as the preparation phase. Once the disruption is actualized, there is an initial impact that degrades performance and a first response by the organization. Next, some time is spent preparing for the recovery and then the recovery phase begins. Finally, after the recovery phase has been fully realized the organization may return to its previous level of performance or fall short of the pre-disruption level. At that time the long-term impacts of the disruption will be assessed and more fully understood.

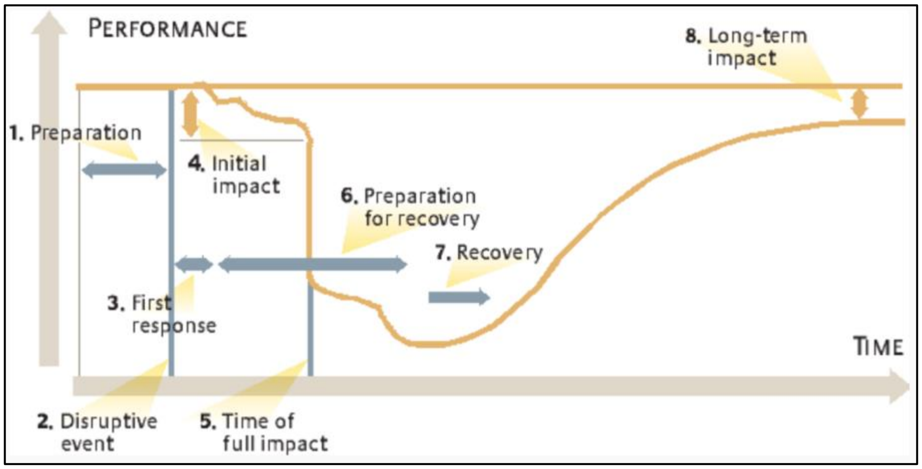

Figure 3.2: Disruption Profile from Sheffi and Rice (2005)

These early graphical measures of resilience were further investigated and then applied to an analysis of the resilience of acute care facilities in Bruneau and Reinhorn (2007), and Tierney and Bruneau (2007) then adapted this framework into the resilience triangle shown in Figure 3.3. Tierney and Bruneau (2007) stated: “Resilience can be measured by the functionality of an infrastructure system after a disaster and also by the time it takes for a system to return to pre-disaster levels of performance.”

The Resilience Triangle displayed in Figure 3.3 (Tierney and Bruneau, 2007) is very similar to Figure 3.1 and the disruption profile in Figure 3.2. The vertical axis is again measured as the quality of infrastructure and time is on the horizontal axis. After a disruption occurs the infrastructure quality is lowered and after a minimum is reached the quality begins to recover to its initial state. This time, however, a triangle is imposed which can be used to geometrically measure both the impact of the disruption and the time to recovery. For example, if the resilience triangle is large, this would be a result of a slow recovery, a large magnitude of impact, or both. On the other hand, a small resilience triangle would result from a fast recovery, small magnitude of impact, or both. Therefore, if there is a standardized performance measure on the vertical axis a small triangle should correspond to an organization that has a greater level of resilience than an organization with a larger resilience triangle.

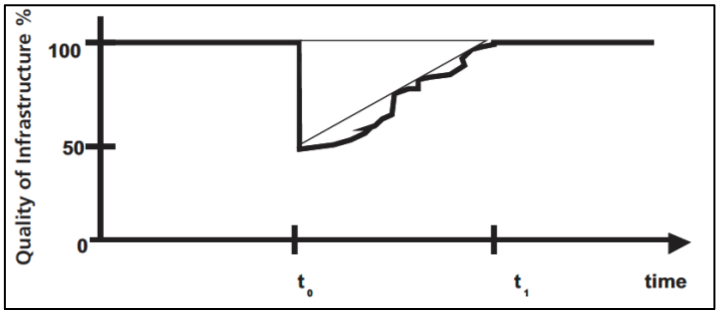

Figure 3.3: Resilience Triangle from Tierney and Bruneau (2007)

The applicability of the resilience triangle as a measure of an organization's resilience has been further explicated in several subsequent research articles (Falasca et al., 2008; Cimellaro et al., 2010; Zobel, 2010; Zobel, 2011; Pant et al., 2013; Carvalho et al., 2011; Guller et al., 2015) which begin to provide a means for quantitative assessment of resilience. For example, Falasca et al. (2008) identified supply chain design characteristics that can be useful when assessing resilience and then integrated them within the resilience triangle framework.

In another example of an empirical application of the resilience triangle approach, Barroso et al. (2015) employed a simulation analysis of a Portugese automotive supply chain. Individual company resilience indices were computed for each company along the supply chain and then the resilience of entire supply chain was estimated by aggregating the individual company index values. In this application the order fulfillment rate of the individual companies (i.e. the percentage of orders fulfilled) was used as the performance measure to compute company-specific resilience index values, and time was measured in days. Figure 3.4 shows an example of one company's performance fluctuation having been exposed to a disruption.

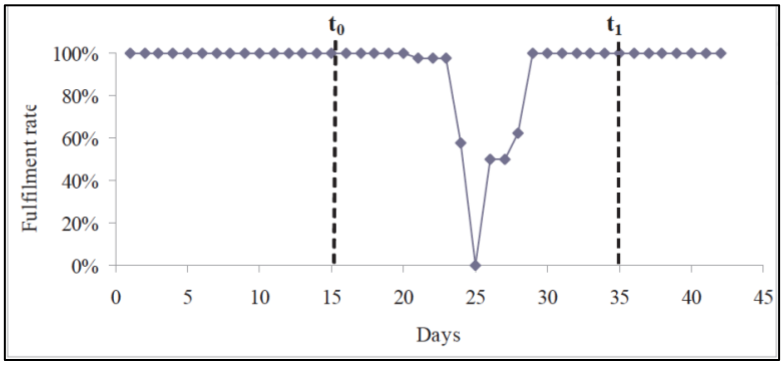

Figure 3.4: Resilience Triangle example from Barroso et al. (2015)

The vertical axis is denoted in percentages that represent the percentages of orders fulfilled by the company. To begin, 100% of orders are being fulfilled. Time is denoted in days, and two specific time periods are demarcated as t_0 and t_1. The time t_0 is "…the lower limit of the time period based on which the company resilience index determined; usually prior to the time instant at which the performance level is affected by the negative effects of the risk." The time t_1 "is the upper limit of the time period based on which the company resilience index is determined; generally corresponds to a time instant at which the performance level is already recovered from the negative effects of the risk." In between time t_0 and t_1 the fulfillment rate drops to several different levels below 100% at different points in time. This performance indicator reaches its lowest level at 25 days when 0% of the orders were fulfilled.

Clearly the performance fluctuations displayed in the graph in Figure 3.4 do not form a perfect triangle. Thus, in order to measure resilience, the authors created an index that involves estimating the area under the curve formed by the fluctuating performance levels:

$$R_i = 1 - \frac{\sum_{t=t_0}^{t_1}\left(1 - \left(\frac{P_{it}}{Pi}\right)\right)}{P_i(t_1 - t_0)}$$

Where:
R_i: is the resilience index of company i;

P_i: is the performance level of company i when it is not affected by the negative effects of a risk;
P_{it}: is the performance level of company i in time period t;
t_o: is the lower limit of the time period based on which the company resilience index is determined (usually prior to the time instant at which the performance level is affected by the negative effects of the risk);
t_1: is the upper limit of the time period based on which the company resilience index is determined (it generally corresponds to a time instant at which the performance level is already recovered from the negative effects of the risk);

The value of R_i will range from 0 to 1, with 0 thus indicating no resilience and 1 indicating full resilience (i.e. no change in performance level during the duration of the disaster). Then, to apply the individual company resilience index estimations to the entire supply chain, four methods are used: (1) linear aggregation, (2) multiplicative aggregation, (3) minimum value aggregation (i.e. the SC resilience is simply equal index of the least resilient company within the SC), and (3) constraint approach (i.e. when one company cannot deliver, the whole supply chain fails).

In another adaptation and application of the resilience triangle, Yang and Xu (2015) assessed the resilience of Chinese agricultural supply chains. More specifically a two-stage grain supply chain consisting of the grain producer and the grain processor is modelled and the impact of government aid on enhancing supply chain resilience is estimated. By examining different recovery paths and resilience triangle sizes, the study showed that optimal allocations of government aid depend strongly on recovery costs associated with backup suppliers. This supports the notion that while multiple sources for grain processors may increase costs over having a single supplier, resilience is overall enhanced by diversifying disaster recovery options.

3.2 Application of the resilience triangle to production agriculture

3.2.1 Step one of the application

In order to apply the resilience triangle method for measuring and comparing levels of farm resilience, several steps were taken. The first step was to identify a specific performance measure that could be utilized for the vertical axis variable. Net farm income was selected as this performance indicator. The Farm Financial Standards Council (FFSC, 2014) classifies net farm income as both a profitability indicator, as well as, a financial performance measure. According to the FFSC, farm performance measures illustrate "… the results of production and financial decisions, over one or more periods of time. Measures of financial performance include the impact of external forces that are beyond anyone's control (drought, grain embargoes, etc.), and the results of operating and financing decisions made in the ordinary course of business." (FFSC, 2014).

Net farm income is indeed a strong indicator of past farm resource management decisions and consequently, it is a performance measure that is capable of measuring the impacts of a shock on the fundamental functioning of the system. If net farm income declines, it will be a result of either an increase in cash farm expenses, a decrease in value of farm production, or both. Because cash farm expenditures represent one subset of the resource decisions made by a farmer, then things like the value of seed and feed purchased, irrigation energy used, cost of labor hired, etc. all provide detailed information about how a particular farmer has made resource allocation decisions while attempting to produce output. Moreover, the value of farm production represents certain outcomes from productive activities like the sales of crops and livestock, collection of government payments, and changes in grain inventories. Net farm income, then, has a unique complexity. It represents both decisions and outcomes. Net farm income is not simply measure of profitability, but rather a robust representation of the resource allocation decisions that an operator has made.

The FFSC does over several warnings about using net farm income for analysis. First, according to the FFSC, "The form of business organization can cause problems for interpretation of this amount. A corporation will include labor payments as a labor cost in their tax-based records unless adjustments are made. Inter-farm comparability must be made with caution whenever different forms of business organization are represented." (FFSC, 2014). Additionally, "The measure is a dollar amount (which may be positive or negative), therefore, it is difficult to compare across farm businesses. It is also impossible to establish one standard for all farm businesses."

In order to account for the difficulties associated with comparing net farm incomes across businesses, real net farm income per acre was used as the performance variable. For this study, net farm income per acre was computed as the reported net farm income divided by the number of acres operated. The number of acres operated was used as the denominator because this study included farms that earned revenue from both crops and livestock. The KFMA dataset that was used for this study contains a variable that is called "Farm Type Code." The values of this variable range from 01 to 53, and each value represents a particular farm type. For example, farm type code "01" represents farms that self-report themselves to be "crop, non-irrigated" operations. As another example, farm type code "19" represents farms that self-report themselves to be "beef backgrounding and finishing" operations. For the dataset available for this study, the majority of farms were either solely crop operations or were crop operations diversified with livestock production.

3.2.2 Step two of application

The second step for this application was to clearly identify shocks that impacted all Kansas farms. Shocks that farmers could potentially encounter can be categorized based on five sources of risk according to Hardaker et al. (2004): production risk, market risk, institutional risk, human risk, and financial risk. Each of these categories can also be broken down into more specific types of risk. For example, shocks stemming from the production risks include weather shocks, pests, and disease. Shocks originating from institutional risk include unexpected changes in pesticide regulations, or changes in the method of distributing government financial assistance for farmers. Market risks generate shocks such as unexpected changes in exchange rates, or a drop in global demand. Combined market and institutional risk might include trade embargos imposed on specific global commodity markets. Personal shocks might include prolonged illness of the farm operator or serious carelessness with expensive machinery and equipment. Financial risks can result in a shock, for example, if there is a spike in interest rates on farm loans, making repayment and profitability harder.

The chosen performance measure, net farm income per acre, is impacted by shocks stemming from all five of the aforementioned categories of risk. Therefore, to identify the periods of shock, the statewide averages of real net farm income per acre (RNFI_A) and nominal net farm income per acre (NNFI_A) were graphed as a time series (Figure 3.5). RNFI_A was used to compare across time and NNFI_A was used to gain insight into the experience of the farmer within each specific year. Both real and nominal net farm income per acre fluctuated rather extensively over this period of time, however, there were two unique time periods that stood out: the drop in net farm income per acre in 1981 and the drop in net farm income per acre in 1998.

To identify the shock periods, the state-wide average values of real and nominal net farm income per acre for 8,233 observations of KFMA farms was graphed from 1973 through 2014 and is shown in Figure 3.5. This graph shows that the lowest state-wide average values of both real and nominal net farm income per acre occurred in 1981. This was one of only two times during this time span that both the average real and the average nominal net farm incomes per acre were negative (the other occurring in 1985). Additionally, the 1980 to 1981 net farm income plunge was in fact the overall largest percentage drop in average real net farm income per acre for the entire time span that was analyzed. After the initial drop in 1981, average nominal net farm income levels did not return to 1979 levels again until 1988, and average real net farm income levels did not reach 1979 levels until 2014. Therefore, based on the precipitous drop in the state-wide average value of net farm income per acre in 1981 and the number of years that sub-trend levels persisted, this was selected as the first aggregate shock period for the analysis.

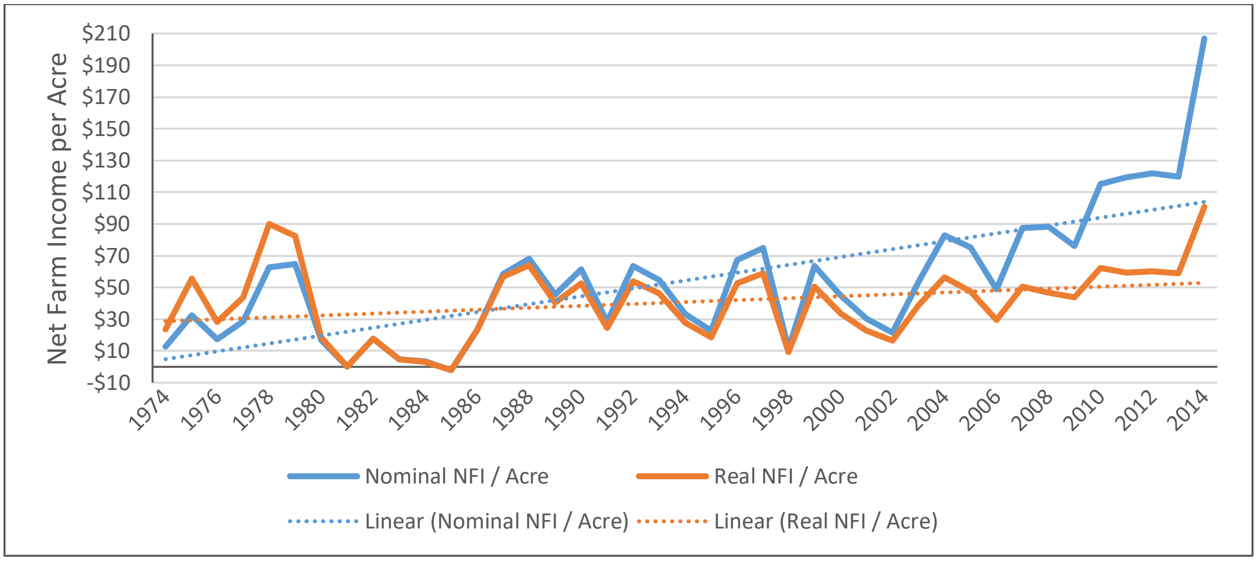

Figure 3.5: Average value of real and nominal net farm income per crop acre, per year, for 8,233 observations of KFMA farms from 1973 through 2014 with linear trend lines

*Real values computed using U.S. Census Bureau Producer Price Index (Base year = 1982:84)

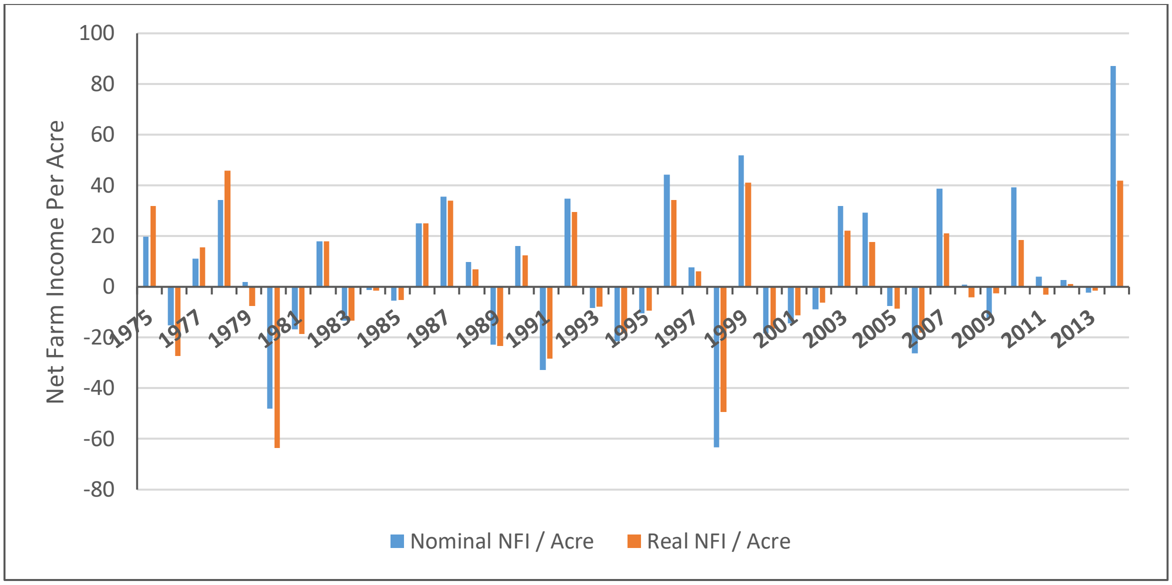

Figure 3.6: Year-to-year changes in real and nominal average net farm income per acre for 8,233 observations of KFMA farms from 1973 through 2014

*Real values computed using U.S. Census Bureau Producer Price Index (Base year = 1982:84)

The second shock period that was chosen for this analysis started in 1998. Going from 1997 to 1998, the percentage changes in real and nominal net farm incomes per acre were more than $40 per acre (Figure 3.6). This happened one other time throughout the time period that was analyzed. In 1998, both real and nominal average net farm income values fell below their respective trend lines (as shown in Figure 3.5) and neither value climbed back above trend again until 2004. This was the second longest period of time during which average net farm income levels dropped below the trend lines. Given the magnitude of the drop and the prolonged depression of net farm income levels, 1998 was chosen as the second shock period.

It was important to also consider that different regions most likely would have had unique experiences during the two periods of shock that were identified by using statewide averages. It is entirely possible that average net farm income was dropping in the western portion of Kansas, while at the same time profitability was booming in the Eastern portion of the state. However, if average net farm incomes are indeed dropping simultaneously across all of the geographic regions of the state, the presence of a major economic shock was most probable. To begin to analyze the potential differences across regions, average values of real and nominal net farm income per acre were computed for six regions of Kansas as defined by the KFMA. The six regions are labelled as northwest (NW), southwest (SW), northcentral (NC), southcentral (SC), northeast (NE), and southeast (SE). The map in Figure 3.7, which was obtained from the KFMA website, shows all of the counties that are included in each of the six regions.

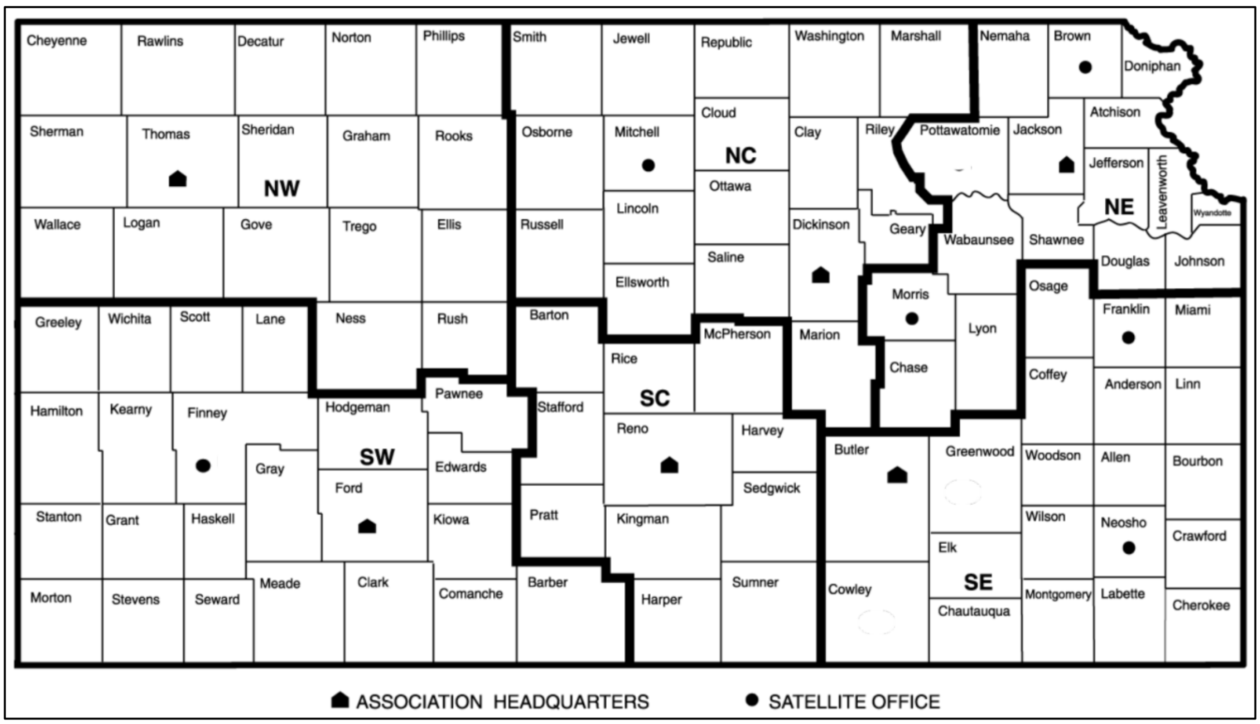

Figure 3.7: Map of Kansas with KFMA-defined regions outlined by counties included in each region (source: https://www.agmanager.info/kfma/map)

The graph in Figure 3.8 shows the year-to-year change in the average real net farm income per acre by geographic region for 4,827 observations of KFMA farms from 1977 to 1987. During this 10-year period, four out of the six regions (NC, SC, NE, SE) experienced their largest drops in average real net farm income per acre going from 1979 to 1980. Then in the very next year the other two regions (NW & SW) experienced their largest drops in average real net farm income per acre. These findings show that the income shock identified above as the first shock period was indeed felt across all regions of Kansas. Also, farms in the northwest and southwest regions appear to have experienced the shock one year after the other regions. This could perhaps imply that farms in this region were better buffered against the shock.

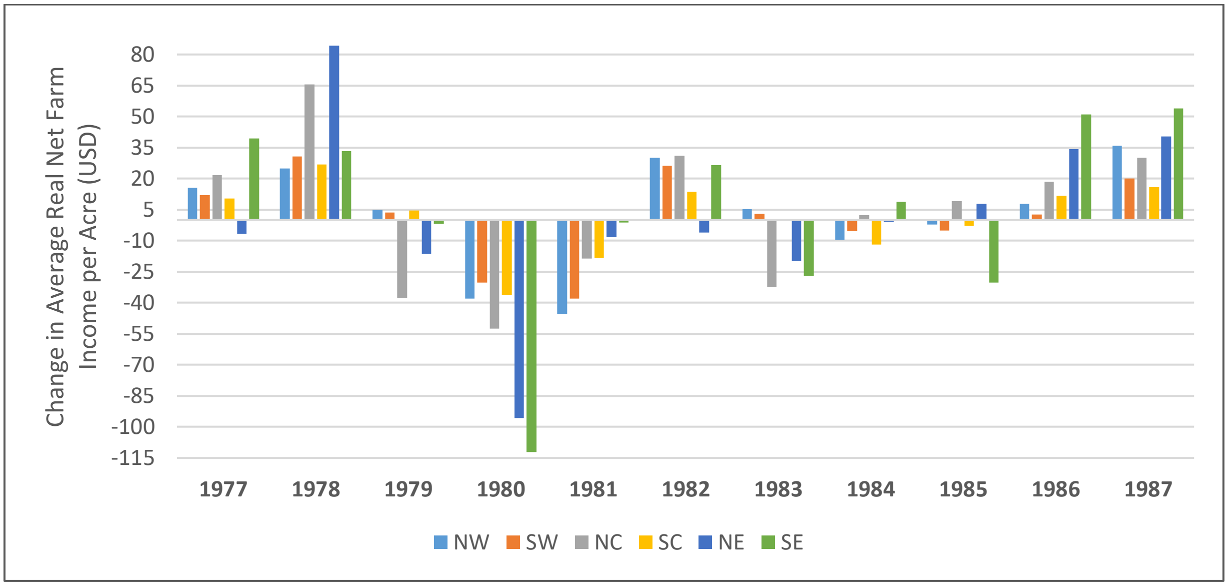

Figure 3.8: Year-to-year change in average real net farm income per acre for 4,827 observations of KFMA farms by geographic region from 1977 through 1987
*Real values computed using U.S. Census Bureau Producer Price Index (Base year = 1982:84)

Moving to the second shock period, Figure 3.9 shows the year-to-year change in the average real net farm income per acre by geographic region for 3,528 observations of KFMA farms from 1994 to 2004. The graph shows that in 1998 the northeast, southeast, and southcentral regions of Kansas experienced their largest drops in net farm income per acre for that 10-year period. Moreover, although in 1999 there was a swift recovery (especially for the southeast region which posted its highest level of net farm income per acre for the ten-year period), during the next three-year period from 2000 to 2002, net farm income consistently declined for all regions except the southcentral region in 2002 (which did improve slightly). Although it was shown above in Figure 3.6 that the drop in net farm income per acre for the entire state of Kansas in 1998 was the second largest in for the years analyzed, this drop appears to have been driven primarily by the northeast, southeast, and southcentral regions, which had larger drops in net farm income than the other three regions. Therefore, when modelling the resilience of individual farms, a categorical conditioning variable was used to denote the geographic region for each specific farm.

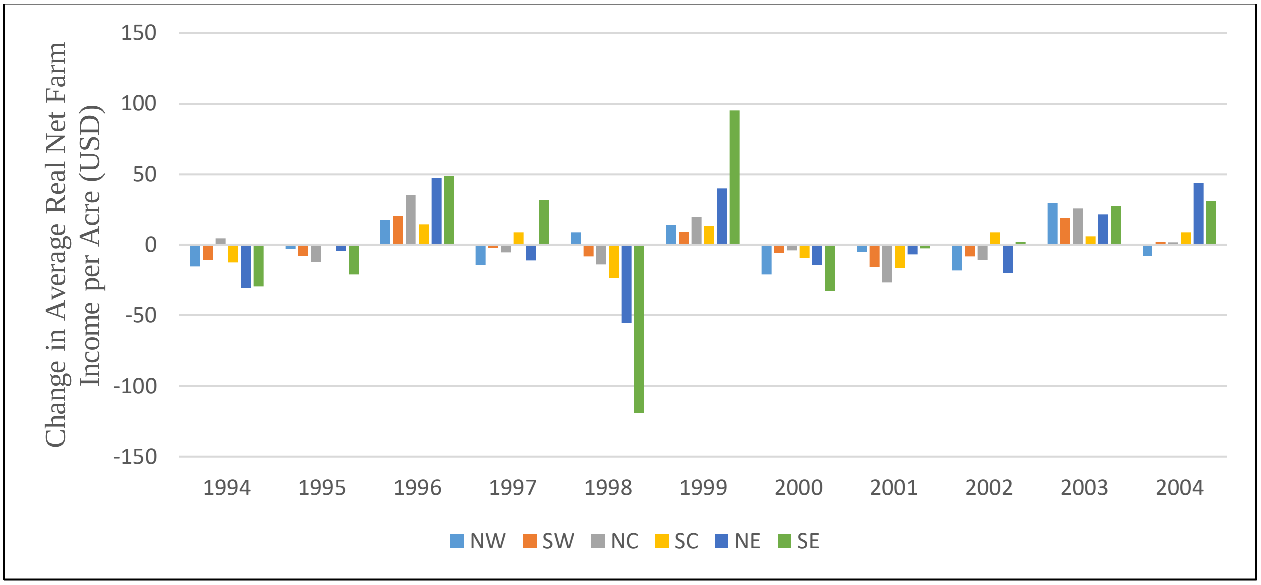

Figure 3.9: Change in average real net farm income per acre from the year prior for 3,528 observations of KFMA farms by geographic region from 1994 through 2004
*Real values computed using U.S. Census Bureau Producer Price Index (Base year = 1982:84)

Finally, in order to determine whether the 1981 and 1998 shocks were caused by revenue declines, cost increases, or both, nominal average value of farm production and nominal average cash farm expenses for 3,528 observations of KFMA farms between 1974 and 2014 was observed in Figure 3.10. The graph shows that the 1980-81 drop in average net farm income was caused by both a decline in value of farm production and an increase in farm expenses. For the second shock period, in 1998, average cash farm expenses actually went down, but there was a simultaneous drop in the average value of farm production. The drop in average value of farm production was greater than the change in cash farm expenses, hence the drop in net farm income. A more detailed description of the causes of the two selected shocks is provided in the Appendix.

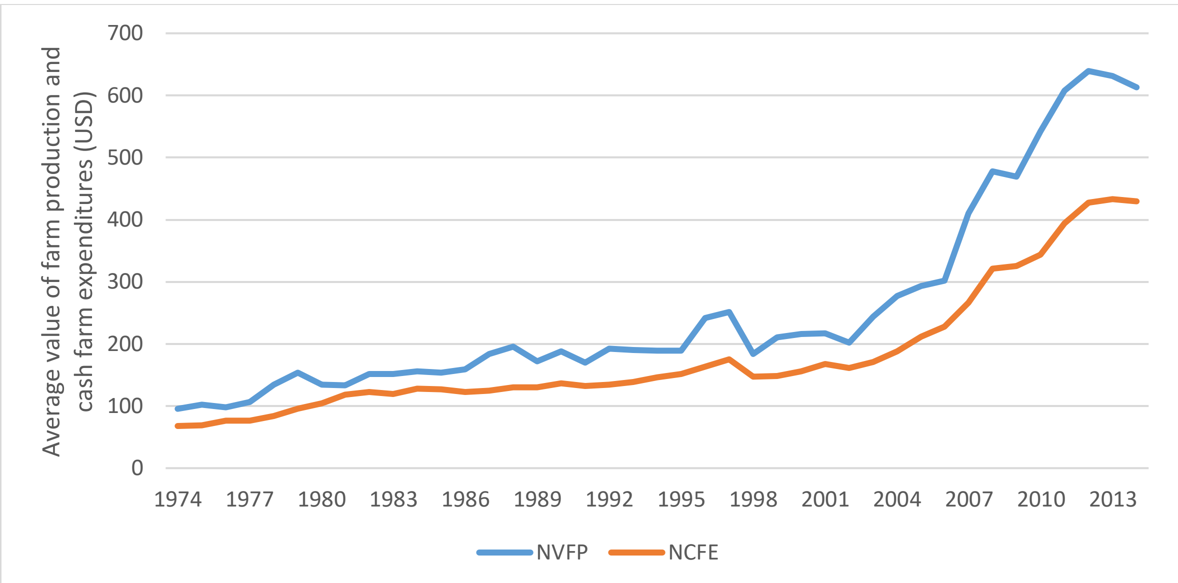

Figure 3.10: Statewide averages of the value of farm production (NVFP) and cash farm expenditures (NCFE) for 8,233 observations of KFMA farms (expressed in nominal dollar values) from 1974 through 2014

3.2.3 Step three of application

The third step for constructing a resilience triangle for a farm, was to mark three distinct time periods: (1) the initial occurrence of the shock (t_P), (2) the period with the lowest experienced level of the performance indicator following the shock (t_L), and (3) the period at which point the performance level of the system has recovered to pre-shock levels (t_N). The identification strategies for the first two time periods have thus far been discussed and established. This section will discuss how the third time period, when the system has recovered, was identified.

Assuming that a farmer is willing and able to continue operations following a shock, a recovery process will begin at some point after t_P. The process and timing of recovery will depend on several factors including the specific type of shock, the condition of the farm prior to the shock, and the aggregate magnitude of the shock. The types of shocks thus far analyzed have been aggregate state-level economic events that impacted all farms on average in the KFMA database. The regional analyses showed that while all farms on average were impacted, the level, timing, and structure of impact varied across the state. Disaggregating further down to the individual farm level will revealed even greater disparity between the recovery processes.

In spite of these variations, in order to construct resilience triangles a single time period must be chosen to act as shock-ending period for the entire state of Kansas. To select this specific time period, the trend lines on Figure 3.5 were analyzed. After the first shock period in 1980, real and nominal average net farm income per acre for all KFMA farms returned to the trend by the year 1987. Although real net farm income per acre does not return to 1979 levels again until 2014, average nominal net farm income per acre does return to pre-shock levels in 1988. Therefore, 1988 was selected as the maximum year for computing resilience triangles for the first shock period.

In regards to the second shock period, real average net farm income per acre drops below the trend line in 1998 and does reach slightly above the trend line the next year. However, after 1999, average real net farm income per acre does not return to above-trend levels until 2004. The average nominal net farm income per acre for all KFMA farms drops below trend in 1998 and then does not reach above the trend line level again until 2004. Therefore, the maximum time period selected for the second shock was 2004.

3.2.4 Additional considerations for the application

Two additional considerations were accounted for when applying the resilience triangle method to production agriculture. First, assume that the triangle in column (a) of Figure 3.11 has the same area as the triangle in column (b). Therefore, both systems would be classified as having equal levels of resilience (discussed in Zobel, 2010), because the two resilience triangles have equal areas. However, even though both of the triangles shaded in gray have the same area, the resilience triangle in column (a) represents a farm that experience a large magnitude of shock, but then was able to recover very quickly. On the other hand, the resilience triangle in column (b) shows a farm that experienced a small initial impact from the shock, but then proceeded through a lengthy recovery time.

There are three alternate conclusions that can be drawn from the situations shown in Figure 3.11. The first potential conclusion is that, as mentioned above, the fact that both resilience triangles have equal areas indicates that the farm represented by column (a) is equally as resilient as the farm represented by column (b). The second potential conclusion is that despite the equality in triangle areas, the farm represented in column (a) is more resilient than the farm represented in column (b) because it recovered faster and will have access to a higher net farm income sooner. As a result, this would mean that a fast recovery has the strongest impact on resilience, so long as the farm remains in operation following the immediate impact of the shock. The third potential conclusion is that the farm represented in column (b) is more resilient than the farm represented in column (a) because it was initially impacted less. Even though it took farm (b) longer to recover to its pre-shock level of net farm income per acre, the small drop in net farm income would have put less strain on the operation immediately following the shock and it therefore had the potential to be more resilient.

The definition of farm resilience that was maintained for this study was the ability of an agricultural production system to return to normal (or improved) operations after having experienced an unexpected economic or environmental shock. This definition therefore considers resilience as *both* the ability to *resist* the initial impact of the shock, as well as, the ability to *recover* from the initial impact of the shock. The resilience triangle approach generates a composite representation of both resistance and recovery time. Hence, regardless of whether the triangle resembles column (a) or column (b), both should be considered as having the same level of resilience. By asserting that the resilience of farm (a) is equal to the resilience of farm (b), a comparison can be made between them to determine if the most resilient farms were those which had the strongest ability to buffer against the initial impact of a shock, or those which had the strongest ability to mobilize resources to adapt to the post-shock environment. In order to make this determination, a series of hypotheses were developed and are discussed in 3.4.

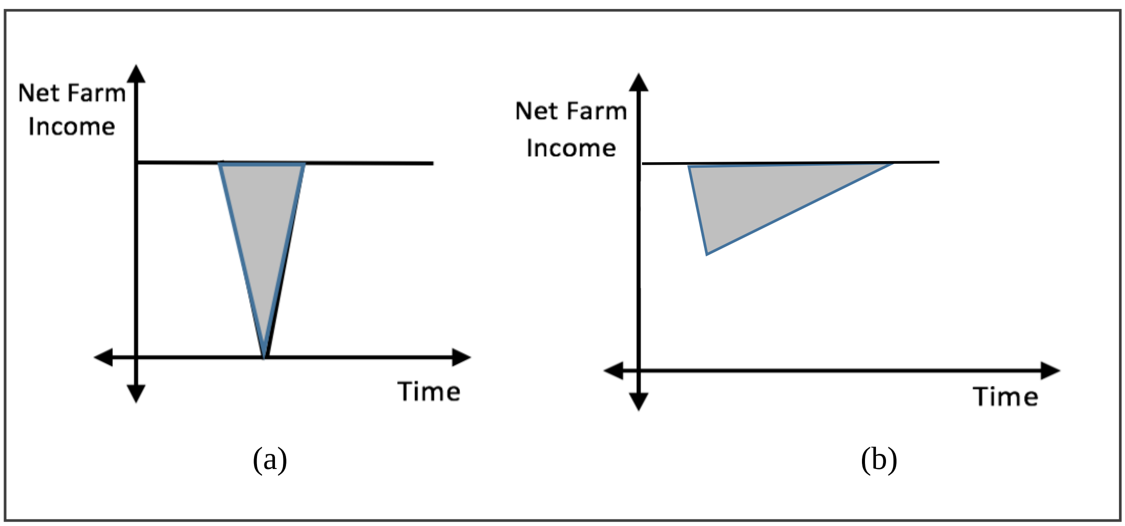

Figure 3.11: Resilience triangles displaying absolute magnitude effect

The next consideration was made to account for the historic volatility seen in net farm income (Figure 3.5). Based on this historic volatility, it seemed highly unlikely that the shock ending value of NFI_{t_P} would ever precisely equal the value of net farm income prior to the shock, NFI_{t_N}. This indicated that the shock-ending net farm income level would almost always be above or below the original value, even if just by a single dollar. The graphs in Figure 3.12 illustrate these two most likely outcomes. The graph in column (a) shows a farm that did not fully recover to pre-shock net farm income levels, but instead set out on a new, lower average level of net farm income. The farm represented by column (b) is illustrated to have recovered to a net farm income level greater than pre-shock levels. Either of these two cases should happen for virtually every single farm. Again, it would be tremendously rare for a farm to return to its exact pre-shock level of net farm income per acre.

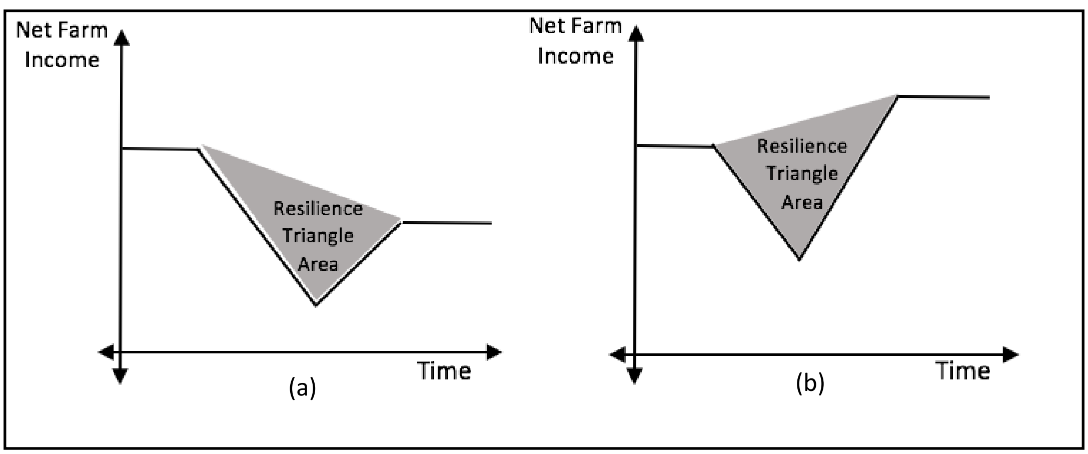

Figure 3.12: Two hypothetical farm resilience triangle shapes

Two potential problems arise as a result of the two scenarios illustrated in Figures 3.11 and 3.12. To explain this scenario, first consider the graph in Figure 3.13. The shaded region labelled “A” is meant to represent the scenario (a) from Figure 3.12. This shows a farm which did not return to its pre-shock performance level. On the other hand, a farm which did return to its pre-shock level of net farm income could be represented by combining the shaded regions "A" and "B." As it turns out, the area of section A is smaller than the areas of sections "A" and "B" combined. In this circumstance, the conclusion that a smaller resilience triangle means greater resilience may not be appropriate. Although a farm with a resilience triangle comprised of sections "A" and "B" would have taken longer to recover, it would perhaps not be appropriate to say that it is less resilient than a farm with a smaller resilience triangle. Moreover, the situation described in Figure 3.11 is not applicable in this case because the farm with resilience triangle "A" did not fully recover. The conclusion drawn from Figure 3.11 is dependent on both farms recovering fully.

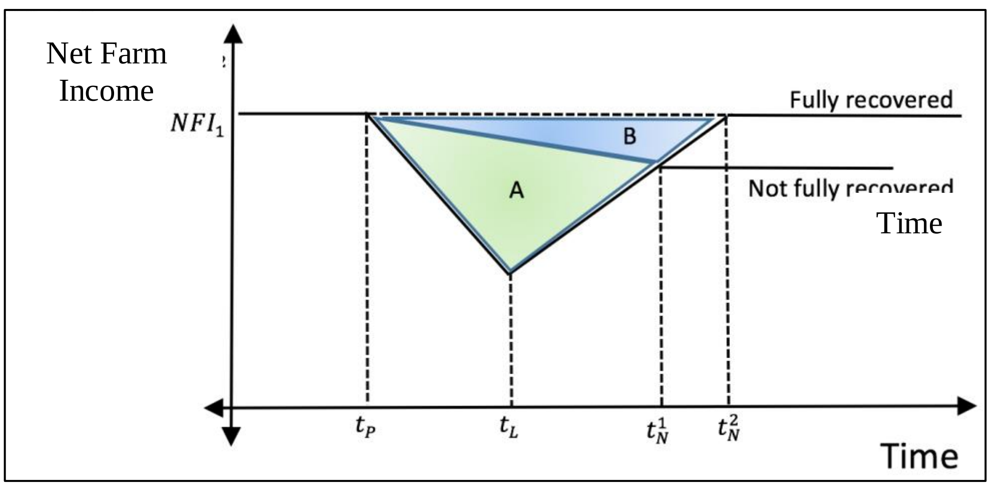

Figure 3.13: Resilience triangle for contractionary recovery

The second complication that arises is concerned with scenario (b) in Figure 3.12. To explain this, consider the graph in Figure 3.14. There are three shaded regions in this graph labelled "A", "B," and "C." In the case when final net farm income is greater than initial net farm income, the resilience triangle area is computed by adding together sections A and B.

However, when final net farm income per acre is equal to the pre-shock level of net farm income per acre, then the resilience triangle area is computed using sections B and C. Because section A is larger than section C, the resilience triangle area for the stronger recovery will be larger than the area for the equal, or same, recovery level. In other words, a farm that recovers to a higher level of net farm income could be considered less resilient (in terms of triangle area) than a farm recovering to its same operating level. Therefore, the standard conclusions that smaller is better with resilience triangles may not be entirely appropriate when using net farm income per acre as a performance measure.

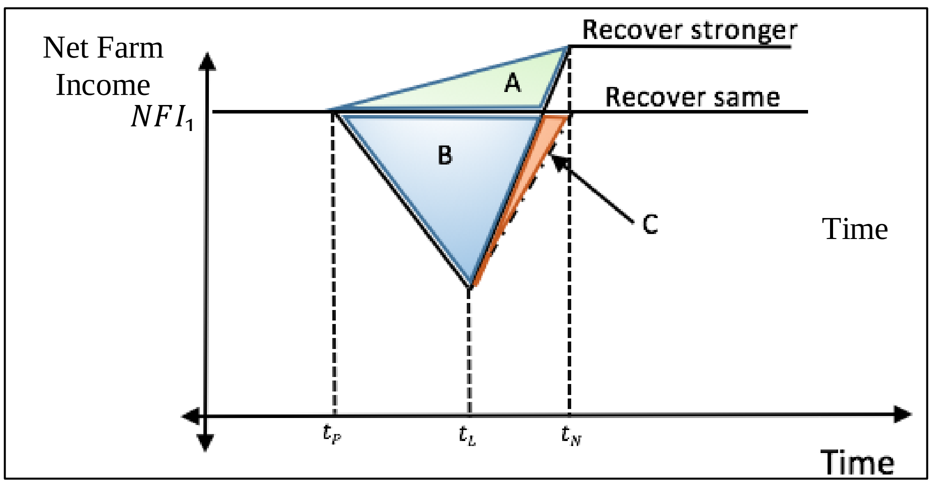

Figure 3.14: Resilience triangle for expansionary recovery

In order to account for the complications that arise from the examples shown in Figures 3.13 and 3.14, several conditions were imposed when computing the resilience index values which are discussed in Section 1 of Chapter 5. One of the conditions imposed was that farms who did not fully recover as shown in Figure 3.13 were assigned a resilience index value of zero. This is consistent with the definition of resilience because the farm did not recover to pre-shock levels of performance. A second condition that was imposed accounted for the complication that arises from Figure 3.14. This condition was that the upper boundary of the third point in the resilience triangle was restricted to the pre-shock level of net farm income per acre. By imposing the two restrictions just mentioned, the result was that two groups of farms emerged: those which were resilient and those which were not. This result is discussed further in section 3.4 with the hypotheses, as well as, Section 1 of Chapter 5.

3.3: Modelling Resilience

While the resilience triangle method is capable of producing an index of resilience that can be used to compare the resilience of one farm to another, it does not fully capture all of the dynamics of system resilience. The index generated from the resilience triangle approach is an *overall* measure of a farm's ability to encounter and recover from a shock, however it does not provide insight about the individual farm characteristics which led to that particular index value. Therefore, to measure farm resilience more comprehensively a model was developed to relate this index value to farm-level characteristics which were identified as the drivers of farm resilience.

The framework for this model is based on the approach presented in Darnhofer (2014). Here, the author proposes that farm resilience is driven by three distinct capabilities. In this context "The term capability is used to denote that it is not an asset or an automatic response that can be deduced from the characteristics of the farm, but the ability to identify opportunities, to mobilise resources, to implement options, to develop processes, to learn as part of an iterative, reflexive process." (Darnhofer, 2014).

The first capability is the farm's buffering capability. This capability is relatable to the first part of the definition of farm resilience: the ability of the farm to withstand the impact of a shock. A farm which has a strong buffering capability will be able to withstand the force of the shock and its level of performance will be minimally impacted. On the other hand, a farm with little buffering capability will be tremendously impacted by the shock and its performance level will be significantly deteriorated. Farms can buffer against shocks in many ways including stockpiling feed for animals, installing irrigation systems, maintaining financial and labor reserves, and operating in several markets.

The second capability that drives farm resilience according to Darnhofer (2014) is the adaptive capability. This "…requires resourcefulness, i.e. 'the ability to identify problems, establish priorities, mobilize resources in face of disruption, to combine experience and knowledge so as to adjust responses to a changing context or to changing preferences by family members.'" (Darnhofer, 2014). After a farm experiences a shock, the environment in which it operates has been fundamentally changed. Therefore, some kind of adaptation is needed. A priori plans must be reconsidered and resource allocation decisions should be made based on the new environment. Although a farm may be able to continue operating for a period of time without adapting, economic theory tells us that eventually competition should drive that farm out of business.

The third capability that drives farm resilience is transformative capability, which is "…the ability to implement radical changes, the ability to create untried beginnings from which to evolve a new way of living." This goes beyond the buffering and adaptive capabilities. It is the fundamental restructuring of the farm to enter new markets, incorporate new production practices, or implement better conservation strategies. In this way a shock will open opportunities for a farm operator to continue producing agricultural products but perhaps in a way not foreseen.

Based on Darnhofer's (2014) capabilities, the following conceptual model is proposed:

$$R_i = f([B_i], [A_i], [T_i], [X_i]) \qquad (1)$$

where $[B_i]$ is a vector of variables that generate buffering capability of farm i, $[A_i]$ is a vector of variables that generate adaptive capability, $[T_i]$ is a vector of variables that generate transformative capability, and $[X_i]$ is a vector of other farm specific characteristics that are hypothesized to affect farm resilience.

3.4 Hypotheses

Based on the literature review in Chapter 2 and the conceptual framework that was developed in Chapter 3, three hypotheses were established. The first hypothesis was generated based on the two potential conclusions that were discussed in section 3.2 regarding the graphs in figure 3.12. For this study, it was hypothesized that among the farms which were resilient (as discussed in section 3.2), buffering capabilities will have had a greater impact on resilience than adaptive capabilities. This supports the conclusion that farms which recover faster will have greater levels of resilience because they have access to higher levels of net farm income per acre sooner. The null hypothesis is shown below as $\mathrm{H1}_0$, which states that the impact of the buffering capabilities on resilience will be equal to the impact of adaptive capabilities on resilience. The alternative hypothesis, $\mathrm{H1}_1$, states that the impact of the buffering capabilities on resilience will be greater than the impact of adaptive capabilities on resilience.

$$\mathrm{H1}_0\text{: } if\ R_i > 0, then\ [B_i] = [A_i]$$

$$\mathrm{H1}_1\text{: } if\ R_i > 0, then\ [B_i] > [A_i]$$

If the null hypothesis, $\mathrm{H1}_0$ is rejected, then this could indicate that a farmer's scarce resources will generate the greatest returns to resilience when they are dedicated to preventing a drop net farm income per acre altogether.

The second hypothesis that was tested for this study was established to determine if buffering capabilities were the most impactful resilience capabilities among the non-resilient farms, or if instead adaptive capabilities were the strongest indicators of non-resilience. In order to test this hypothesis, resilience index values were computed for farms that were originally assigned a value of zero resilience. This was done by using the same method as the one used for the resilient farms, however rather than imposing a restriction on the upper boundary of net farm income per acre, a time restriction was imposed so that the final time period was restricted to the state average shock-ending time period. This is described in further detail in Section 1 of Chapter 5.

Among the farms that did not fully recover from the shock, a larger resilience triangle would indicate lower levels of resilience. A larger resilience triangle in this case would be caused only by a large magnitude of impact, a slow recovery, or both. If a farm did not fully recover, then this would mean that it did not have sufficient buffering capabilities or sufficient adaptive capabilities, or both capabilities were simultaneously lacking. The hypothesis for this study was that farms with the lowest buffering capabilities would also have the lowest levels of resilience index values. If a farm has strong buffering capabilities, it will be able to withstand the shock, and there will be a minimal drop in performance. However, without strong buffering capabilities, a farm would be severely impacted by the shock and performance would drop substantially. By determining if buffering capabilities were indeed the most impactful among the non-resilient farms, then this aligns with the first hypothesis that buffering against a shock is most important for overall resilience.

The null hypothesis is shown as $\mathrm{H2}_0$, which states that for farms who were considered non-resilient, then buffering capabilities and adaptive capabilities would have had equal impacts on the resilient index values. The alternative hypothesis is shown as $\mathrm{H2}_1$ states that for farms who were considered non-resilient, then buffering capabilities would have a stronger impact on resilience index values as compared to adaptive capabilities.

$$\mathrm{H2}_0\text{: } if\ R_i = 0, then\ [B_i] = [A_i]$$

$$\text{H2}_1\text{:} \, if \; R_i = 0, then \; [B_i] > [A_i]$$

The third hypothesis that was tested for this study was that the farms which did not recover would have lower levels of both buffering and adaptive capabilities as compared to the farms which did fully recover. If a farm had a resilience index value of zero, this meant that it did not recover from the shock and was therefore declared non-resilient. In order for this to have happened, the non-resilient farm must have had either insufficient buffering capabilities, insufficient adaptive capabilities, or both. The null hypothesis, H3_0, states that the buffering and adaptive capabilities of resilient farms are not statistically different from the buffering and adaptive capabilities of non-resilient farms. The alternative hypothesis, H3_1, states that the buffering and adaptive capabilities of resilient farms are greater than those of the non-resilient farms.

$$\text{H3}_0\text{:} \, if \; R_i > 0 \; and \; R_j = 0, then \; [B_i] = [B_j] \; \& \; [A_i] = [A_j]$$

$$\text{H3}_0\text{:} \, if \; R_i > 0 \; and \; R_j = 0, then \; [B_i] > [B_j] \; \& \; [A_i] > [A_j]$$

If the null hypothesis, H3_0, is rejected, then this could indicate that strengthening buffering and adaptive capabilities will strengthen overall resilience.

The results of testing the aforementioned hypotheses will have implications for agricultural producers, agricultural lenders, and policy makers. The contribution to agricultural producers is to help strengthen farm resilience by identifying the characteristics that define the most resilient farms. If the most resilient farms exhibit certain characteristics, then less-resilient producers can work to better allocate resources to achieve a similar mix of buffering, adaptive, and transformative capabilities. The results will also help producers to determine which capabilities are the most impactful and will most efficiently enhance resilience. The contribution to agricultural lenders is that by ranking farms from most to least resilient, a lender will have another means of assessing the riskiness of a loan to an individual borrower. If the borrower exhibits the characteristics of the least resilient farms, then a lender will know to take extra precautions before offering a loan (or could perhaps deny the loan application entirely). On the other hand, if a farm exhibits the characteristics of the most resilient farms then a lender can feel more assured offering a loan. Finally, policy makers will benefit from the results of this study because they will provide a better understanding about how to best support farm resilience. If buffering capabilities have the greatest impact on overall resilience, then policies should be aimed at bolstering these capabilities. If buffering and adaptive capabilities are found to equally impact resilience, then policies should direct resources equally to enhancing both.

Chapter 4: Data

The data for this research was obtained from the Kansas Farm Management Association, which contains detailed farm-level financial and production information for more than 3000 farms in Kansas between 1973 and 2014. While this dataset is expansive, only certain observations were utilized in this analysis. The data was first restricted to only those farms that produced crops during either of the two shocks. Next, farms were used only if they were in operation for all the years of either shock period 1 or shock period 2. Finally, farms were omitted if they had a negative net farm income at the start of their respective shock period. If a farm already has a negative net farm income when the shock starts it was assumed to have not been operating at a normal level of performance.

In total there were 879 observations for this study; 270 from the first shock period and 609 from the second shock period. Table 4.1 presents the summary statistics by region for the farms selected in the first shock period. Kansas is a diverse state, so in order to disaggregate the data, the KFMA separates farms into six geographic regions: northwest (NW), southwest (SW), north central (NC), south central (SC), northeast (NE), and southeast (SE).

During the first shock period, the southeast and southcentral regions had the greatest number of observations, while the northwest region had the least number of observations. The largest farms were in the northwest and southwest, while the smallest farms were in the northcentral and southcentral regions (as measured by average number of acres managed). The farms with the highest real value of farm production during this time period were in the southwest and northeast regions, and farms in the southcentral had the lowest average real value of farm production. On a per-acre basis, however, farms in the northeast and southeast had the highest average real value of farm production while farms in the northwest had the lowest.

Similarly farms in the northeast and southeast regions had the highest average real net farm incomes, both in total and on a per-acre basis, while farms in the northwest and southwest had the lowest values. There was little variation in the average age across regions, although the largest gap was between an average age of 49 in the southwest and 54 in the northwest.

The bottom four rows in Table 4.1 show the percentage of farms within each region that were categorized in this study as crop-only, crop-mainly, crop-livestock, and general. In order to assign a farm to one of these four classifications, the KFMA farm-type classification system was used as follows. The KFMA farm classification system assigns a number to each operator based on the farm's primary productive activity. For example, non-irrigated crop-only farms are labelled "01," dairy farms are labelled "06," feeder pig production is labelled "08," etc. These farm classification codes allow farms to be separated into relatively specific groups. The KFMA assigns these numbers based on the following conditions. First, if a farming operation utilized 70% or more of its labor on one activity during a particular year, it was classified as a single farm type (i.e. dryland crop farm, irrigated crop farm, cowherd, dairy, etc.). If there were two production activities that each utilized 35% or more of labor, the farm was classified as a multiple farm type (i.e. crop-cowherd, crop-backgrounding, crop-dairy, etc.). If the operation was diversified such that each production activity accounted for less than 35% of the labor usage, the farm was defined as a "general farm." These general farms had at least three primary production activities and included farms with less than 500 acres managed, up to farms with more than 2500 acres managed.

In this study, farms were aggregated into the following two groups by using the KFMA farm classification number system: (1) crop-only, and (2) diversified farms. For a farm to be placed into the first group "crop-only," the farm must have been assigned the KFMA farm-type code of either “01-Crop, Non-Irrigated” or “02 – Crop, Irrigated” for each year of the shock. These farms did not engage in livestock operations at all during either shock period, and so are thus “crop-only.” Next, to assign a farm into the diversified farm group, three additional categories were created and then relevant observations were combined into the single diversified group. First, a group named “crop-livestock” was found by observing the mode of the KFMA farm classification number for the 8 years that comprised the first shock period and the 10 years for the second shock period. During the course of either shock period, if the value of the mode was 21-29 or 39-44 (which are all of the farm-type numbers that involve both crop and livestock production), then that farm was placed into group (2) “crop-livestock.” Next, in order to be placed in the group “crop-mainly,” the mode of the KFMA-assigned farm type must have been either “01” or “02,” but at some point during the shock the farm classification was neither “01” nor “02” (thus indicating that during one or more of the shock years the farm would have also been classified as crop-livestock). This type of farm operation was classified as “crop-mainly.” Finally, if the mode of the farm-type number for the entire shock period was “35 – General Farm,” then the farm was placed into the fourth group, general farm. Summary statistics are presented in Table 4.1.

Table 4.1: Summary Statistics by Geographic Region, First Shock Period
*Real values computed using U.S. Census Bureau Producer Price Index (Base year = 1982:84)

	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
Number of Observations	17	35	32	65	47	68
Average Acres Managed	2484	2252	1170	1189	1264	1364
Average Real VFP*	$170,955	$205,029	$138,973	$146,718	$197,265	$155,844
Average Real VFP / Acre	$128	$175	$216	$168	$373	$310
Average Real NFI	$27,758	$32,049	$28,835	$27,126	$35,345	$31,274
Average Real NFI / Acre	$21	$23	$45	$33	$67	$60
Average Age	49	54	51	52	50	52
Crop-Only Farms	24%	60%	24%	55%	40%	37%
Diversified Farms	76%	40%	76%	45%	60%	63%

Next, Table 4.2 provides regional summary statistics for the second shock period. The greatest number of observations were from the southeast region (283 observations) while the southwest had the least number of observations (37 observations). The largest farms were, like the first shock period, in the northwest and southwest regions, while the smallest farms were in the northeast region. Farms in the northwest had the largest absolute value for the average real value of farm production ($223,061) while farms in the northcentral had the lowest value for the average real value of farm production ($159,917). On a per-acre basis, however, farms in the northeast and southeast regions had the highest average real value of farm production at $239 and $248 respectively. Farms in the southwest region had the lowest average real value of farm production per-acre, at $106. Farms in the northwest also had the highest average real net farm income and farms in the northcentral had the lowest. However, the highest values of average real net farm income per-acre were seen in the northeast and southeast regions. Similar to the first shock there is not much difference in average age from one region to another, although in this shock period the average age of farmers was above 53 in all regions (as compared to 49 in the first shock period) and the greatest average age was 58 (compared to 54 in the first shock period).

Table 4.2: Summary Statistics by Geographic Region, Second Shock Period
*Real values computed using U.S. Census Bureau Producer Price Index

	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
Number of Observations	37	30	104	134	103	200
Average Acres Managed	2791.4	2307.2	1604.9	1750.6	1479.5	1851.7
Average Real VFP	$223,061*	$170,631	$159,917	$173,817	$194,891	$177,010
Average Real VFP / Acre	$124	$106	$166	$122	$239	$248
Average Real NFI	$42,358	$33,675	$29,041	$37,495	$41,497	$41,390
Average Real NFI / Acre	$25	$23	$32	$26	$41	$49
Average Age	52	58	53	54	54	55
Crop-Only Farms	68%	63%	59%	89%	72%	65%
Diversified Farms	32%	37%	41%	11%	28%	35%

Chapter 5: Analysis

5.1: Calculation of resilience index values

In order to calculate resilience index values for all N observations, several steps were taken. The first step was to set time boundaries that would establish the three points of the resilience triangle. The graph in Figure 5.1 shows a resilience triangle framework with real net farm income per acre on the vertical axis and three distinct time periods labelled along the horizontal axis. The first time period, t_P identifies the level of real net farm income per acre immediately before the start of the shock. The time period, t_L, represents the time when performance (real net farm income per acre) is at its lowest value after the shock has occurred. Finally, t_N is the time period when the shock period ends and the farm has recovered from the shock.

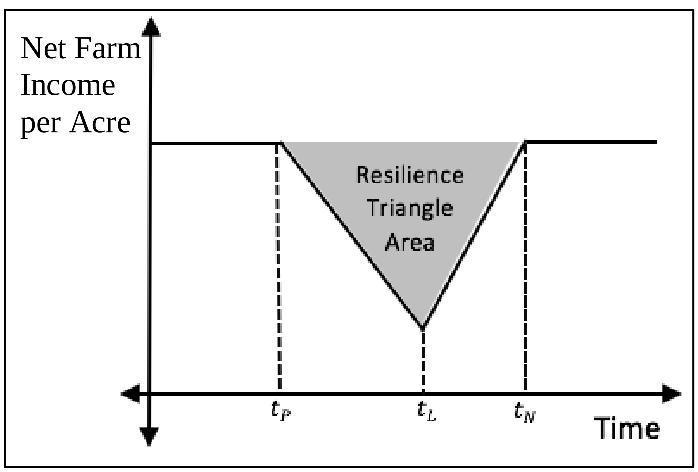

Figure 5.1: Resilience Triangle with three time periods specified

First, in order to determine time period t_P, the level of real net farm income per acre at each had to meet the following requirements:

$$NFI_{t_P-1} \leq NFI_{t_P} \qquad \& \qquad NFI_{t_{P+1}} < NFI_{t_P} \tag{i}$$

The first condition (i) dictates that the net farm income at the starting point of the shock must be greater than or equal to net farm income in the period immediately preceding it and must also be strictly greater than net farm income in the period immediately after. In this way, the initial impact of the shock is specific to the individual farm. It is possible that some farms enter the shock sooner, and others later. For both shock periods, the initial starting date is determined by restricting the search for the starting time period from $\bar{t}_{P-3}$ to $\bar{t}_{P+3}$. Next, condition (ii) states that the net farm income level at the worst part of the shock should be at a minimum.

$$NFI_{t_L} < NFI_{t_{L+1}} \qquad \& \qquad NFI_{t_L} < NFI_{t_{L-1}} \tag{ii}$$

In order to identify the third time period, t_N, two additional conditions were imposed. The third condition (iii) states that the maximum number of years that a farm has to recover from the shock is restricted to the number of years that farms on average across the state took to recover.

$$\max t_N \leq state\ average\ \bar{t}_N \tag{iii}$$

One result from condition (iii) is that it is possible for NFI_{t_N} to be less than NFI_{t_P}. In that case, the resilience of the farm was still calculated, however it was also assigned a binary variable of zero, as it did not recover from the shock. The farms for which $t_N = \bar{t}_N$ were considered to be non-resilient as discussed in Chapter 3, which is consistent with the definition of agricultural resilience that was used for this study.

It is also possible that net farm income could have risen above pre-shock levels prior to the state average number of shock years, $\bar{t}_N$. In these cases, condition (iv) states that the final level of net farm income per acre is set equal to the value net farm income at the pre-shock time period, t_P. This condition was imposed to account for the complication illustrated in figure 3.14.

In addition, these farms were assigned a binary variable of 1 to indicate that they were in fact resilient.

$$\max NFI_{t_N} = NFI_{t_P} \tag{iv}$$

To compute resilience triangles using real net farm income per acre, the following specification of Heron's formula was used:

$$Area = \left(\frac{t_L(NFI_1 - NFI_3) + t_P(NFI_3 - NFI_2) + t_N(NFI_2 - NFI_1)}{2}\right) \tag{2}$$

where NFI_n refers to real net farm income per acre at time n, and each subscript corresponds to a particular time period. NFI_1 corresponds to net farm income per acre at time period t_P, NFI_2 corresponds to t_L, and NFI_3 goes with t_N (see Figure 5.2). This formula will compute the area of the triangle formed, whether net farm income per acre is positive or negative.

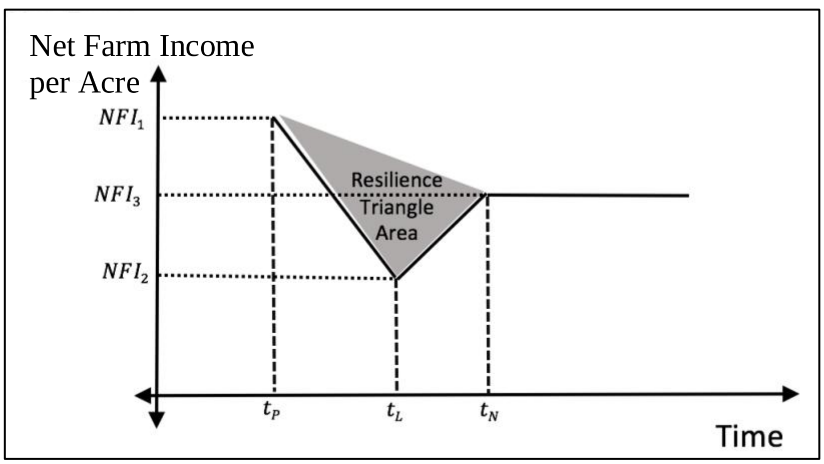

Figure 5.2: Graphical representation of equation (5)

Finally, the resilience index value was generated by taking the inverse of the resilience triangle area:

$$R_i = \left(\frac{t_L(NFI_1 - NFI_3) + t_P(NFI_3 - NFI_2) + t_N(NFI_2 - NFI_1)}{2}\right)^{-1} \tag{3}$$

Using equation (3), the resilience index value, R_i will be large if the area of the triangle is small. This offers a more intuitive interpretation of the number used to express the level of resilience. The concept of the resilience triangle is that small triangles (i.e. small area) correspond to better resilience, and large triangles (i.e. large areas) correspond to less resilient farms. However, by using equation (3), the most resilient farms will have the highest R_i and the least resilient farms will have the smallest value of R_i.

5.2: Econometric model

A fractional logit regression model was used for this study and estimation was conducted using Stata. This type of regression was chosen because the values of R_i that were computed using equation (3) ranged between zero and one. The fractional logit regression was developed in Papke and Wooldridge (1996) to model employee participation rates in employer-sponsored 401(k) retirement plans. Since then, this type of regression has been used in a number of settings for which the dependent variable ranges between zero and one.

The fractional logit regression stems from the generalized linear model (GLM) approach. The GLM approach was developed because there are many economic variables of interest for which an ordinary least squares approach would not be appropriate because the variable in question is not distributed normally. This would be appropriate, for example, when the dependent variable is restricted to positive values (like number of children in a family), or when the dependent variable is a binary or fractional variable. One technique for dealing with binary and fractional dependent variables has been to estimate a general linear model by simply transforming the dependent variable. For example, applying a commonly used log transformation to the resilience index values from equation (3) would be shown as: $\log[R_i/(1 - R_i)]$. After this transformation the dependent variable now ranges over all real values, while the values of R_i would still only range between zero and one. This would immediately cause a problem in the current study, as Wooldridge (2001) points out, because resilience index values can take on the value of both zero and one.

Generalized Linear Models are based on simple linear models; however, they have the advantage that they can accommodate the types of dependent variables that were just discussed. To explain this further, equation (4) shows equation (1) specified as a linear model, where the expected value of the resilience index, R_i, is equal to the mean μ_i.

$$\mathrm{E}(R_i) = \mu_i = \sum_1^k x_{ik}\beta_k\,; \qquad i = 1, \ldots, N \tag{4}$$

In equation (4), the ordinary linear model assumes standard normal distribution and the predicted values of R_i will range over all real values, which in this study is unwanted. With a GLM approach, the predicted values of the dependent variable, $E(R_i)$ are restricted to a particular range by using a link function.

In "Generalized Linear Models, 2nd Edition" by McCullagh and Nelder (1989), the process of implementing a link function is shown by using a three-part specification: (A) the random component; (B) the systematic Component; and (C) the link function. This process is illustrated for the current study with equations (5) through (8) below. Based on the linear specification in equation (4), equation (5) shows that the expected value of the resilience index is the mean, μ, and it is assumed that the resilience index, R, is independently and normally distributed. Equation (6) shows that the left-hand side variables are assumed to produce a linear predictor, η and equation (7) shows that the expected outcome (i.e. the mean, μ) is therefore also equal to the linear predictions, η, of equation (6).

$$\mathrm{E}(R) = \mu; \tag{5}$$

$$\eta = \sum_1^k x_k\beta_k\,; \tag{6}$$

$$\mu = \eta, \tag{7}$$

Based on the linear specification in equation (4), the predicted values, η, would not be restricted to fall between zero and one. Therefore, to accommodate the fact that the resilience index values must only take values between zero and one, a link function is used as shown in equation (8).

$$\eta_i = g(\mu_i), \tag{8}$$

According to equation (8) the predicted values from the model, η_i, are equal to the expected mean values, μ_i, which are represented as a function $g(\cdot)$. This new function, $g(\cdot)$, can be any monotonic differentiable function and as a result the distribution for the dependent variable, R_i, can be any from the exponential family.

The link function that was used for this study was the logit specification, based on Papke and Wooldridge (1996). This is shown in equation (9):

$$\mathrm{E}(R_i | C_i) = G(C_i\beta) = \exp(C_i\beta) / [1 + \exp(C_i\beta)], \qquad i = 1, \dots, N, \tag{9}$$

where $0 \leq R_i \leq 1$ is the resilience index value for farm i, C_i is a $(1 \times k)$ matrix of the explanatory variables described in equation (1), N is the sample size, and $G(\cdot)$ is a link function that satisfies $0 < G(z) < 1$ for all $z \in \mathbb{R}$. According to Wooldridge (2001), the specification in equation (9) ensures that the predicted values of R_i will range between zero and one.

Papke and Wooldridge (1996) state that estimates of β in equation (9) that are generated using QMLE are robust and efficient. The likelihood function used for this study was based on Papke and Wooldridge (1996), as well as, Wooldridge (2001), Ramalho, Ramalho, and Murteira (2009), and the Stata user manual (2015). Equation (10) can be found in the Stata user manual as the general form of the log-likelihood function that is maximized for fractional models. Then equation (11) shows the specification for this study. As stated above, the link function, $G(\cdot)$, that was used for this study was the logit specification in equation (9).

$$\ln L = \sum_{j=1}^{N} w_j y_j \ln\{\mathrm{G}(x_j'\beta)\} + w_j(1-y_j)\ln\{1-G(x_j'\beta)\}, \tag{10}$$

$$\ln L = \sum_{i}^{N} R_i \ln\{\mathrm{G}(C_i\beta)\} + (1-R_i)\ln\{1-G(C_i\beta)\}, \qquad i = 1, \ldots, N, \tag{11}$$

One drawback when using this estimation technique for a logistic model is illustrated in Papke and Wooldridge (1996). They show that the variance equation for the dependent variable that comes from using GLM generally fails. To overcome this problem, they suggest "…an asymptotically robust inference for the conditional mean parameters" (Papke and Wooldridge, 1996), which provides a valid and consistent estimate of the variance. Using the "fracreg" command in Stata to estimate this model, robust standard errors are computed by default.

The parameter estimates that are obtained from estimating a fractional logit regression cannot be directly interpreted, however, according to Wooldridge (2001), this can be managed by calculating the marginal effects. Based on Wooldridge (2001):

$$\frac{\partial \mathrm{E}(R_i|\, C_i)}{\partial x_k} = \frac{\partial G(C_i\beta)}{\partial x_k} = \frac{\partial\left\{\frac{\exp(C_i\beta)}{[1+\exp(C_i\beta)]}\right\}}{\partial x_k} \tag{12}$$

$$\frac{\partial \mathrm{E}(R_i|\, C_i)}{\partial x_k} = \beta_k \times \frac{\exp(C_i\beta)}{[1+\exp(C_i\beta)]} \times \frac{1}{[1+\exp(C_i\beta)]} \tag{13}$$

$$\frac{\partial \mathrm{E}(R_i|\, C_i)}{\partial x_k} = \beta_k g(C_i\beta), \text{ where } g(C_i\beta) = \exp(C_i\beta)\,/[1+\exp(C_i\beta)]^2 \tag{14}$$

In equations (12) through (14) the denominator, x_k, is referring to individual component, k, of the C_i matrix of independent variables. Wooldridge (2001) posits that the marginal effects in equation (12) can be somewhat comparable to the estimates from OLS when the sample averages are used. In order to calculate the marginal effects for this study, the "margins" command in Stata was used post-estimation.

5.3: Explanatory variables

In order to select the explanatory variables for the vectors in C_i, the resilience triangle method was first integrated with the three buffering capabilities. To help explain how this was achieved, Figure 5.3 presents a resilience triangle with the three resilience capabilities shown as spanning three distinct time periods. First, the buffer capability, B_i, is illustrated to begin at some initial pre-shock time period and end at time period t_P. Next, the adaptive capability, A_i, is shown to begin at time period t_P and end at period t_L. Finally, the transformative capability is shown to begin at period t_L and end at t_N.

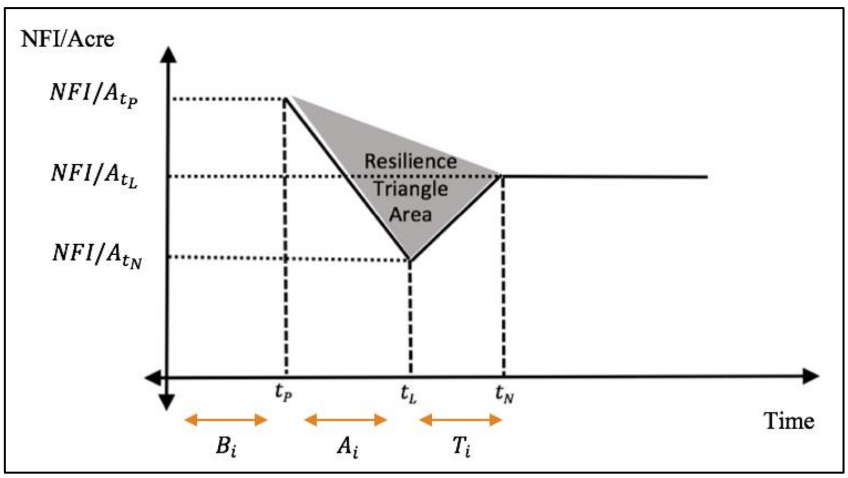

Figure 5.3: Resilience capabilities and resilience triangle integration

Intuitively, buffer capabilities are understood as being developed leading up to a shock and then utilized immediately following a shock. It is important to note that buffer capabilities do not represent a stock of assets, but rather a collection of skills, talents, resources, and possibilities that a farmer has assembled in an effort to minimize the losses resulting from having experienced a shock. If a producer's net income is in fact impacted as a result of environmental or economic shock, then the producer will begin implementing adaptive measures. For whatever reason, the buffering capabilities did not mitigate 100% of the impact of the shock on net farm income. Consequently, the producers will go through a period of reallocating resources and adapting to new strategies in an effort to stop the losses and continue operating indefinitely. After the producer has reached the turning point when net farm income stops declining and begins to return to pre-shock levels, the farm begins to transform into a new system of resources. Although the farm still retains essentially the same function of producing food, the environment in which it operates is new, the technologies available have most likely advanced, and the mix of resources available have adjusted.

5.3.1 Buffering Capabilities

After establishing the time frames within which the three capabilities are enacted, the dependent variables were then selected based on several bodies of literature including general economic theory, agricultural resilience theories, and agricultural risk management research. To begin, the first variable that was chosen to measure a farm's buffer capability, $[B_i]$ was an index of diversification for the three-year period leading up to the shock. Previous studies have shown that the diversification of farm production can enhance the ability to respond to changes in consumer preferences and weather financial shocks (Featherstone and Moss, 1990; Lin, 2011; Kremen and Miles, 2012). Diversification can offer a financial hedge, improve conservation of the land, and better enable a farmer to respond quickly to policy changes. On the other hand, diversification generally increases costs, increases risk from exposure to new or varied markets, and quite often requires significant investment in both human and physical capital. While diversification most certainly has both pros and cons, the farm resilience-enhancing benefits may potentially outweigh the costs. Farms that have been successfully running diversified operations should already be more capable of persisting when confronted with a shock, compared to farms that are less diversified. In other words, the benefits of the ability to produce a variety of outputs from a particular plot of farmland, is hypothesized to outweigh the costs.

For the buffering capability, diversification was computed as the average level of crop acre diversification across the three years leading up to the shock period. An index of crop acre diversification was computed using a method similar to the Herfindahl-Herschman (HH) index, as shown in equation (15). Then, the average value of the crop diversification index was computed using the values from the three years prior to the shock, as shown in equation (16).

$$D_i^n = \left(\sum_{k=1}^{20}\left(\frac{TAP_k}{TAP}\right)^2\right) \tag{15}$$

$$ADiv_i = \left(\frac{1}{3}\right) \times \left[\sum_{n=t_{P-1}}^{t_{p-3}} D_i^n\right] \tag{16}$$

where D_i^n is the diversification level of farm i at time period n, TAP_k refers to the total acres planted to crop k, and TAP is the total acres planted. The k crops included dry and irrigated acres of: wheat, corn, grain sorghum, soybeans, sugar beets, alfalfa, silage, other grain, other hay, and other cash crops. By taking the inverse of this summation, higher levels of D_i will indicate more diversification. For example, if a farm had dedicated 100% of acres to a single crop then $D_i = 1$. Alternatively, if a farm had dedicated 40%, 30%, 20%, and 10% of acres to different crops, then the concentration ratio would be 3.33.

The second variable chosen to represent buffering capabilities was the average debt to asset ratio for the three years immediately before the shock (DAR_i). It is common practice for modern farmers to use leverage in their operations for a variety of purposes. A loan could be used to buy a tractor, purchase farm land, cover cash expenses, or improve structures. It is even used as a means to ride out periods of low net farm income until returns are large enough to repay the debt. However, when a farmer becomes significantly over-burdened with the cost of borrowing, the buffering capability of that farmer deteriorates. Indeed, researchers have shown that lower debt-to-asset ratios correspond to greater profitability (Purdy et al., 1997; Mishra et al., 2009).

The KFMA dataset contains values for current and noncurrent assets, as well as short term debt level and long term debt for each farm. Using this data, the second buffer capability variable was computed as shown in equation (17):

$$DAR_i = \left(\frac{1}{3}\right) \times \left[\sum_{n=t_{P-1}}^{t_{P-3}} \left(\frac{ST\ Debt + LT\ Debt}{Total\ Assets}\right)_{i,n}\right] \qquad (17)$$

The third variable chosen to represent buffering capabilities was the average real value of beginning crop inventories for the three years prior to the shock. Excess capacity is identified in Rose (2009) as a resilience capability that enhances and protects a system, and Darnhofer (2014) discusses excess capacity as a buffering capability. If a farmer is able to maintain a persistent stockpile of excess crops, this shows that the farmer is able to manage production so that abundance is continual. Grain inventories are assets that are available during times of economic and environmental hardship, and therefore act as a buffering capability.

The KFMA dataset contains annual values for beginning and ending stocks of grain, hay & forage, and cash crops for all farms used in the analysis. Using this data, the third buffer capability variable was computed as shown in equation (18):

$$CropInv_i = \left(\frac{1}{3}\right) \times \left[\sum_{n=t_{P-1}}^{t_{P-3}} (BGI + BHFI + BCC\ )_{i,n}\right] \qquad (18)$$

where BGI is the beginning grain inventory, $BHFI$ is the beginning hay and forage inventory, and BCC is the beginning crop inventory, all expressed in terms of real dollars.

5.3.2 Adaptive Capabilities

The driving motivation behind the selection process for the adaptive capabilities vector, $[A_i]$, was that adaptive capabilities are employed when adjustments are needed. According to

Rose (2009) and Darnhofer (2014), "Changes implemented may cover new technologies, a change in product characteristics, the identification and establishment of new marketing channels, an increase in storage facilities, the new pooling of resources with other farmers or making production processes more flexible." Moreover, Darnhofer (2014) states that "…the changes implemented are marginal, i.e. they do not bring about something that is radically new."

The first variable selected to represent $[A_i]$ was the change in the level of revenue diversification (DVR_i) experienced by farm i from period t_P to t_L. There are many ways that a farming operation can diversify revenue streams including off-farm income sources (Huffman and Lange, 1989; Mishra and Goodwin, 1997; Ahearn et al., 2006), vertical integration (i.e. livestock and feed-grains), government support (Dimitri et al., 2005), agro-tourism (Amanor-Boadu, 2013), renting land and buildings (Darnhofer, 2010), and engaging in the production of alternative crops. By engaging in revenue diversification in response to a shock, a farmer is making small adjustments in an effort to stop the downward progression of net farm income.

The KFMA database includes information on the value of grains produced, but also contains information on revenue earned from other sources including livestock production, off-farm work, government payments, and other product sales. Similar to equation (16), the revenue diversification index was:

$$D_i^t = \sum_{k=1}^{5} \left(\frac{A_i^k}{TR_i}\right)^2 \quad (19)$$

$$\Delta RDiv_i = D_i^{t_N} - D_i^{t_P} \quad (20)$$

where in equation (19) D_i^t is the diversification index value for farm i at time period t, A_i^k is the total revenue earned by farm i from activity k in that time period, and TR_i is the total revenue earned by farm i in that time period. Then, equation (20) shows that the value for DVA_i is computed by subtracting the diversification index from time period t_P from the diversification index value at time period t_N.

The second variable chosen to represent the adaptive capabilities was the change in the average level of the crop-acre diversification index from the three years prior to time period t_L, $ChgADiv_i$. This variable was computed as shown in equations (21) and (22):

$$ADiv_i{}' = \left(\frac{1}{t_L - t_P}\right) \times \left[\sum_{n=t_P}^{t_L} D_i^n\right] \quad (21)$$

$$\Delta ADiv_i = ADiv_i' - ADiv_i \quad (22)$$

Darnhofer (2014) mentions that “Adaptive capability is linked to …flexibility and diversity,” and that important changes involve “…making production processes more flexible.” While pre-shock crop acre diversification shows that flexibility can be a buffering capability, the change in the acre diversification level shows how a farmer has responded to the shock.

The third and final variable chosen to represent the adaptive capabilities was selected to act as a gauge of a farm’s conservation efforts. Conservation has been identified as a buffering capability in previous research (Rose, 2009; Speranza, 2013: Darnhofer, 2014). At the farm level, conservation can occur in a variety of ways including low-till/no-till production practices (Knowler and Bradshaw, 2006), crop rotation practices, and installing efficient watering systems. Economically, conservation practices could also be defined within the context of cost minimization. Farms which achieve the lowest production costs per acre have exhibited an innate ability to conserve their available resources and maximize the output per unit of input (Mishra, 1999). Therefore, the final adaptive capability variable was the change in the average operating expense ratio from the three years prior to the shock, to the average operating expense ratio between periods t_P and t_L. This variable was computed as shown in equations (23), (24), and (25):

$$OER_i = \left(\frac{1}{3}\right) \times \left[\sum_{n=t_{P-1}}^{t_P} \left(\frac{Operating\ Expenses}{Value\ of\ Farm\ Production}\right)_{i,n}\right] \tag{23}$$

$$OER_i{}' = \left(\frac{1}{t_L - t_P}\right) \times \left[\sum_{n=t_P}^{t_L} \left(\frac{Operating\ Expenses}{Value\ of\ Farm\ Production}\right)_{i,n}\right] \tag{24}$$

$$\Delta OER_i = OER_i{}' - OER_i \tag{25}$$

where OER_i is the average operating expense ratio for the three years prior to the shock and $OER_i{}'$ is the average operating expense ratio from time period t_P to time period t_L.

5.3.3 Transformative Capability

Similar to the adaptive capability, the transformative capability of a farm, $[T_i]$, is fundamentally dynamic. It is the ability "…to create untried beginnings from which to evolve a new way of living" (Walker et al., 2004, Darnhofer, 2014). Transformations can occur for a number of reasons, whether it was crisis or a planned process. Transformative capability is different from adaptive capability, however, because it is more permanent. While adaptation is measured as small marginal changes to accommodate the changing environmental factors in the moment, the transformative capability of a farm is driven by its ability to fundamentally change. As shown in Figure 5.3, after integrating the resilience capabilities framework into the resilience triangle framework, the transformative capability is most present from time period t_L to t_P. In this way, the transformative capability is being shown to have been triggered by a crisis. After the farm has stopped the fall of net farm income, the transformation begins as the recovery takes hold.

The first variable used to represent the transformative capabilities vector measured whether or not a farm had changed its "farm type code" after the shock. To do this, the statistical mode of the reported farm type codes for the three years prior to the shock were compared to the statistical mode of the reported farm type codes for the three years immediately after recovery from the shock. If the statistical mode changed, then this variable took the value "1" to indicate that the farm type had changed. This would mean that the farm had transformed over the course of the shock into one which focused its productive efforts primarily on a set of outputs that were different from the pre-shock period. In order to make this transformation, it is assumed that a farmer would most likely have had to invest in capital, both physical and human, to try something new.

The second variable chosen to represent the transformative capabilities measured if the farm was larger after the shock than before, in terms of acres operated. If the farm becomes larger after the shock, it will have transformed into a new type of operation, with a different set of parameters and new challenges. With a larger farm there are more resources to manage and economies of scale to gain. The value of this variable was the difference between the acres operated at time period t_N and the acres operated at time t_P.

5.3.4 Other Variables

The first two variables in the X_i matrix are the age of the primary operator (Age_i) and the square of the age (Age_i^2). Economic theory posits that as economic systems continue to operate successfully through time, the ability of the system's participants to allocate resources successfully are compounded as human capital is acquired. In addition to greater stocks of human capital, older farmers generally have greater access to credit, have better access to markets, and possess more liquid assets than younger farmers. Mishra et al (1999) find that older farmers are generally more profitable than younger farmers, and Goodwin et al (2002) find that yield performance generally tends to improve with years of experience of the farmer. On the other hand, Tauer (1995) discusses how productivity may decline as a farmer ages. The health complications that often accompany old age would undoubtedly make it difficult to meet the physical demands of running a farm indefinitely. To account for both of these potentials, the age of the farmer at the start of the shock period and the square of the age at the start of the shock period were included in the X_i matrix.

Next, a binary variable was also included in the X_i matrix to control for the region where the farm was located. The land area of Kansas is more than 80,000 square miles and according to the Kansas Department of Agriculture approximately 88% of that land area (46 million acres) is used for agricultural purposes. The geography and climate over this expansive state is quite varied. Soil compositions vary substantially from primarily silt loam in the west to clay in the east. In addition, farmers in the eastern portion of the state benefit from strong annual rainfalls, while the climate in the southwestern portion of the state are quite arid. To counter this, however, many farmers in the southwest are able to exploit the Ogallala aquifer for irrigation purposes. In fact, farmers through much of central and western Kansas have access to the Ogallala aquifer. However, the saturated thickness varies substantially by region ranging from nearly 500 feet in some counties to less than 50 in others (US Geological Survey, 2009).
In order to account for these regional differences, dummy variables were used to categorize each farm into one of six regions based on the KFMA framework.

The fourth variable included in the X_i matrix was the squared value of the number of acres managed. Although economies of scale have driven the average farm size to become larger (as shown in the summary statistics in chapter 4 and Featherstone et al., 2005), it could be argued that if a farm becomes overly large then shocks will have a magnified impact.

The final variable included in the X_i matrix was a binary time period indicator ($Time$). The first shock in this study occurred in the late 1970's and early 1980's, while the second shock occurred in the mid 1990's. There are many differences between these two time periods in regards to agricultural production in Kansas. Between that time period there were three different federal farm bills, many more farmers began implementing conservation techniques like no-till/low-till, and usage of advanced satellite tracking and mapping technologies increased substantially. Therefore, to account for the time-specific environmental factors observations from the first shock period were identified by $Time$ = 1.

Table 5.1: List of variables used to represent resilience capabilities

Vectors	Var ID	Observed variables
$[B_i]$	DVA_i	Average diversification of crop acres for three years prior to the shock
	DAR_i	Average debt to asset ratio for the three years prior to the shock
	$CropInv_i$	Average value of crop inventories for the three years prior to the shock
$[A_i]$	$\Delta RDiv_i$	Change in average revenue diversification, pre-shock to post-shock
	$\Delta ADiv_i$	Change in average crop-acre diversification, pre-shock to post-shock
	ΔOER_i	Change in average operating expense ratio, pre-shock to post-shock
$[T_i]$	New_i	Change to a new farm type, pre-shock to post-recovery
	$Size_i$	Change in the size of the farm, pre-shock to post-recovery
$[X_i]$	Age_i	Age of farmer at start of shock
	Age_i^2	Square of the age of farm at the start of the shock
	$[Reg_i]$	Region (NW, SW, NC, SC, NE, SE)
	$Acre^2$	Squared value of acres operated
	$Time$	First shock period is $Time$ = 1

Chapter 6: Results

6.1: Resilience Index Values

Resilience triangle areas were computed at the individual farm level, and average values are shown by region in Table 6.1. This results show that the most resilient regions in the first shock period were the southwest and northwest regions, and the least resilient were the southcentral and northcentral. For the second shock period the most resilient regions were again the northwest and southwest, and the least resilient regions were the northeast and southeast. The resilience index values increased going from shock 1 to shock 2 for all regions, although the increases were not of equal magnitude for all regions as shown by the percentage change values in the 5th row of Table 6.1. The largest increases in average resilience index values were seen in the southcentral (277% increase) and northcentral regions (185% increase), while the northeast (27% increase) and southeast (50%) regions had the lowest percentage increase in resilience index value.

Table 6.1: Average resilience index values by region (Index values multiplied by 100)

	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
Avg. R_i	**0.405**	**0.693**	**0.371**	**0.484**	**0.429**	**0.265**
(1980)	(35%)*	(20%)	(19%)	(9%)	(17%)	(19%)
Avg. R_i	**1.254**	**1.051**	**0.736**	**2.123**	**0.443**	**1.116**
(1998)	(30%)*	(27%)	(23%)	(20%)	(26%)	(23%)

* Values are the percentage of farms in each region that fully recovered from the shock

Table 6.1 also shows the percentage of observations in each region for which the farm recovered to a level of net farm income per acre that was equal to or greater than net farm income at the start of the shock (i.e. observations for which $NFI_{t_N} \geq NFI_{t_P}$ & $t_N \leq \bar{t}_N$). For the first shock, the region with the greatest percentage of farms fully recovering was the northwest (35%) and the region with the lowest level of farms fully recovering was the southcentral (11%). Going from the first shock period to the second, five of the six regions experienced an increase in the percentage of farms that fully recovered, and only the northwest region experienced a decline in the percentage of farms that fully recovered. In spite of this decline, the northwest region still had the highest percentage of farms fully recovered in the second shock period (30%), and again the southcentral region still had the lowest percentage of farms fully recovering (21%).

Average resilience index values were also computed by farm classification and the results are shown in Table 6.2. During the first shock period the crop-only farms were on average the most resilient and had 19% of farms fully recovered. The crop-mainly farms had the next highest average resilience levels, but the lowest percentage of fully recovered farms (15%). The crop-livestock farms had the third highest average resilience level and 17% of farms fully recovered, and the general farms had the lowest average resilience level but the highest percentage of farms fully recovered. The crop-only farms increased in average resilience going from the first to the second shock, although only by 4.3%. The crop-mainly farms saw a 94% increase in average resilience index values going from the first to the second shock period, and the percentage of farms fully recovering increased as well, going up to 31%. The average resilience level for the crop-livestock farms increased by 81% going from the first to the second shock period and the percentage of farms that fully recovered also increased to 43%. Finally, all four of the classification groups saw average resilience index values increase going from the first to the second shock. The group of farms classified as crop-mainly had the highest percentage increase in resilience index values going from shock 1 to shock 2, and the general farms had the lowest increase. Finally, it should be noted that although the average resilience index value for the general farm category increased by 74%, and 100% of these farms were fully recovered in the second shock period, there was in fact only a single observation of general farms in the second shock period.

Table 6.2: Average resilience index values by farm classification

	Crop-Only	Diversified
Avg. R_i (1980)	**0.751**	**0.376**
% Fully Recovered	19.2%	16%
Avg. R_i (1998)	**0.779**	**0.801**
% Fully Recovered	18%	37%
% Δ R_i from 1980 to 1998	3.7%	113%

To summarize tables 6.1 and 6.2, going from the first to the second shock period, the average level of resilience (as measured by the resilience index values) increased in 5 out of the 6 regions, as well as in 3 out of 4 farm types. The greatest improvements in resilience were observed in the southcentral and northcentral regions. Although the average resilience index values for these regions were not the highest for either of the two shock periods and these regions did not have the highest percentage of farms fully recovering, the largest percentage increase in the average resilience values were seen in these regions. In terms of farm-types, the largest increase in the average level of resilience was seen for the crop-mainly farms, which also had the highest average level of resilience in the second shock period. The average level of resilience amongst the crop only farms did not increase much going from the first shock to the second shock, however, these types of farms had the highest average level of resilience in the first shock and the second highest average level of resilience in second shock. This indicates that crop-mainly and crop only farms had high levels of resilience, and maintained these high levels through time, especially in the southcentral and northcentral regions, which saw dramatic increases in these types of farms going from the first to the second shock period (Tables 4.1 and 4.2).

6.2 Resilience Capabilities Variables

Summary statistics by region for the variables chosen to represent buffering, adaptive, and transformative capabilities are presented in Table 6.3 for the first shock and Table 6.4 for the second shock. Table 6.3 shows that the highest average debt-to-asset ratio leading up to the first shock was seen in the northwest region of Kansas (37%), while the lowest value was seen in the northeast region (23%). Farms in the northeast region were the most acreage diversified prior to the shock, with a diversification index value of 0.313, whereas farms in the northwest were the least diversified (index value of 0.567). The highest real average values of crop inventories were held by farmers in the southwest and the lowest value of crop inventories were held by farms in the northcentral. For all regions except the southeast, the change in the revenue diversification was negative, indicating a trend towards greater levels of revenue diversification during the shock. Likewise, all regions experienced a negative change in the values of the acreage diversification index, with the northwest experiencing the greatest change. Negative values for this variable indicate that farmers became more diversified during the shock period. The average operating expense ratio declined for all regions, with the largest decline occurring in the northwest region and the smallest decline happening in the southeast region. The region with the greatest percentage of farms changing from one farm type to another was the northcentral region (48% of farms) and the southcentral region saw the smallest percentage of farms changing (18%). The majority of farms in all regions became larger, particularly in the northcentral region where 79% of farms had more acres managed after the shock compared to before the shock. Finally, the percentage of farms transforming to a higher level of average real net farm income per acre was highest in the northwest region (35%) and lowest in the southcentral region (11%).

Table 6.3: Averages of resilience capabilities variables for the first shock period

	NW	SW	NC	SC	NE	SE
3-yr. Debt to Asset	37%	28%	26%	31%	24%	26%
3-yr. Acre Diversification	0.567	0.486	0.370	0.488	0.310	0.368
3-yr. Crop Inventory $	$70,963	$90,966	$35,851	$40,962	$56,324	$60,738
Chg. Rev. Diversification	-0.014	-0.403	-0.057	-0.015	-0.050	0.011
Chg. Acre Diversification	-0.090	-0.056	-0.003	-0.014	-0.030	-0.022
Chg. Expense ratio	-0.180	-0.122	-0.070	-0.106	-0.064	-0.042
Chg. Farm Type	47%	31%	48%	18%	46%	32%
Chg. Farm Size	59%	63%	79%	68%	75%	73%
Fully Recovered	35%	20%	18%	11%	17%	20%

Moving next to the second shock period, Table 6.4 shows that the northcentral region had the highest pre-shock debt-to-asset ratio (37%) and the northeast region again had the lowest (24%). Farms in the northeast were also the most acreage-diversified (index value of 0.331) and farms in the southwest were the least diversified. Farms in the northwest had the highest real value of crop inventory prior to the shock ($95,165) and farms in the northcentral again had the lowest. The change in the revenue diversification was negative for the southwest and southcentral regions, and positive for the rest. This indicates that during the second shock period, farmers in the southwest and southcentral increased revenue diversification while farmers in the other four regions decreased their levels of revenue diversification. All regions had negative changes in the acreage diversification except the northeast region, which saw an increase in the index value (i.e. northeast became less acreage diversified). The southwest region had the highest percentage of farms which changed into a new farm type at 53%, whereas the southcentral saw the smallest percentage change. Similar to the first shock period, the majority of farms in all six regions became larger after the shock as compared to before, particularly in the southcentral region where 63% of farms were larger after the shock. Finally, in the second shock period all regions had more than 20% of farms experience a transformation to a higher level of average real net farm income per acre, with the highest percentage again being in the northwest region.

Table 6.4: Averages of resilience capabilities variables for the second shock period

	NW	SW	NC	SC	NE	SE
3-yr. Debt to Asset	32%	26%	37%	31%	24%	29%
3-yr. Acre Diversification	0.429	0.481	0.354	0.467	0.331	0.364
3-yr. Crop Inventory $	$95,165	$80,444	$41,810	$53,360	$75,871	$79,067
Chg. Rev. Diversification	0.116	-0.058	0.009	-0.023	0.023	0.011
Chg. Acre Diversification	-0.047	-0.044	-0.022	-0.038	0.004	-0.011
Chg. Expense Ratio	0.038	0.018	0.074	0.051	0.117	0.081
Chg. Farm Type	14%	53%	38%	11%	18%	24%
Chg. Farm Size	59%	60%	59%	63%	55%	61%
Fully Recovered	30%	27%	23%	21%	26%	23%

In addition to computing the average values of the resilience capabilities across regions and shock periods, correlation coefficients were computed to determine if there could be potential multicollinearity present in the econometric estimations. The results are shown below in Table 6.5 for the resilient farms and 6.6 for the non-resilient farms. In both cases, the correlation coefficients are less than 0.40 for all of the resilience capabilities. The highest correlation was -0.388, which was among the non-resilient farms between the acre diversification buffering capability and the acre diversification adaptive capability. The second highest correlation was -0.297 among resilient farms between the revenue and acre diversification adaptive capability variables. The third highest correlation, -0.188, was among the non-resilient farms between the debt to asset ratio and acre diversification buffering capabilities.

Table 6.5: Correlation coefficients for resilient farms, both shock periods

	DAR_i	DVA_i	$CropInv_i$	$\Delta RDiv_i$	$\Delta ADiv_i$	ΔOER_i
DAR_i	1.00					
DVA_i	0.03	1.00				
$CropInv_i$	-0.10	-0.13	1.00			
$\Delta RDiv_i$	-0.01	-0.13	0.05	1.00		
$\Delta ADiv_i$	0.00	-0.15	-0.05	-0.29	1.00	
ΔOER_i	0.01	-0.16	0.11	0.08	-0.01	1.00

Table 6.6: Correlation coefficients for non-resilient farms, both shock periods

	DAR_i	DVA_i	$CropInv_i$	$\Delta RDiv_i$	$\Delta ADiv_i$	ΔOER_i
DAR_i	1.00					
DVA_i	0.07	1.00				
$CropInv_i$	-0.18	-0.18	1.00			
$\Delta RDiv_i$	0.00	-0.04	0.01	1.00		
$\Delta ADiv_i$	-0.04	-0.38	0.08	0.15	1.00	
ΔOER_i	0.02	0.02	-0.00	0.03	0.09	1.00

6.3: Econometric Model Results and Hypothesis Testing

The first hypothesis was tested by estimating the model specified as equation (26), which is shown below. The results from this estimation are presented in Table 6.7.

$$R_i = fn([B_i], [A_i], [X_i]),\ \forall\, R_i > 0 \qquad (26)$$

These results were computed using the Stata command “fracreg logit” which computes a logistic fractional response model. The results in Table 6.7 show that all three of the buffering capabilities were statistically significant. The marginal effect for the pre-shock debt to asset ratio is negative and indicates that a one percent increase in the debt to asset ratio corresponded with a 0.1% decline in the resilience index value. The marginal effect on the acreage diversification buffering capability indicates that a one percent increase in the acre diversification index will corresponded with a 0.3% increase in resilience. The intuitive result is that among the farms that were resilient during both shock periods, those which were less diversified during the three years prior to the shock also had higher resilience index values. Finally, the estimates for the crop inventory buffering variable indicated that a one percent decrease in the average value of crop inventories for the three years prior to the shock corresponded with a 0.1% decrease in the resilience index values among resilient farms. This result indicates that maintaining a stockpile of crops may not be a strong buffering capability.

Among the adaptive capabilities, the change in revenue diversification and the change in the operating expense ratio were both statistically significant. All three of the marginal effects, however, were smaller than 0.1%, indicating that adaptive capabilities were not strong predictors of resilience, but they were overall impactful on resilience. The coefficient estimate for the revenue diversification adaptive capability variable was negative indicating that among the resilient farms, those which became more diversified also had higher levels of resilience. The coefficient estimate for the operating expense ratio variable was also negative indicating that among the resilient farms, those which were able to reduce their operating expense ratio the most were also the most resilient. Although it was not statistically significant, the sign on the change in acreage diversification variable indicates that farms which became more diversified were also most resilient.

The coefficient estimates for the age variables were also statistically significant, but their signs were opposite. The marginal effect that was estimated for the age variable indicated that a one percent increase in the age of the farmer at the start of the shock corresponded with a 3.6% decrease in the resilience index value. On the other hand, the marginal effect that was estimated for the squared value of the starting age indicated that a one percent increase in the squared value of the starting age corresponded with a 1.7% increase in the resilience index value. The squared value of acres operated was not statistically significant, but it was positive which would indicate that larger farms were more resilient.

Among the regional categorical variables, the estimation results indicate that all five regions were more resilient than the southeastern region, however, the coefficient for the northeastern region was not statistically significant. The coefficient that was estimated for the binary variable that was used to account for the two different time periods was statistically significant and negative. This would indicate that among the resilient farms, the observations from the second shock period were more resilient than those from the first shock period. In order to better determine the different impacts of the two shock periods, two additional models were estimated. The first additional model included only observations from the first shock period, and the second additional model included observations only from the second shock period. The results of these two models are shown in Table 6.8 and 6.9.

Table 6.7: Fractional response logit model estimates for resilient farms from both shock periods; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	-0.586	0.250	-2.340	0.019	-1.077	-0.095	-0.001	-2.420
DVA_i	0.912	0.436	2.090	0.036	0.058	1.767	0.003	1.960
$CropInv_i$	0.000	0.000	-3.320	0.001	0.000	0.000	-0.001	-3.670
$\Delta RDiv_i$	-0.077	0.033	-2.330	0.020	-0.142	-0.012	0.000	1.590
$\Delta ADiv_i$	-0.524	0.825	-0.630	0.526	-2.142	1.094	0.000	0.510
ΔOER_i	-1.914	0.596	-3.210	0.001	-3.083	-0.745	0.000	-2.000
Age_i	-0.100	0.054	-1.830	0.067	-0.206	0.007	-0.036	-1.770
Age_i^2	0.001	0.001	1.660	0.097	0.000	0.002	0.017	1.590
$Acre^2$	0.000	0.000	0.830	0.409	0.000	0.000	0.000	0.790
NW	0.482	0.296	1.630	0.104	-0.098	1.063	0.004	1.780
SW	0.514	0.224	2.290	0.022	0.075	0.953	0.005	3.570
NC	0.332	0.211	1.570	0.116	-0.082	0.746	0.003	1.940
SC	0.386	0.165	2.340	0.019	0.063	0.708	0.003	4.390
NE	0.080	0.217	0.370	0.713	-0.346	0.506	0.001	0.130
$Time$	-0.772	0.183	-4.220	0.000	-1.130	-0.413	-	-
$Constant$	-0.772	0.183	-4.220	0.000	-1.130	-0.413	0.007	16.77

The results in Table 6.8 show that among resilient farms during the first shock period, the average level of acre diversification was positive and statistically significant. The marginal effects indicate that a one percent increase in the acre diversification index corresponded with a 0.4% increase in the resilience index value. Because higher values of the acre diversification index correspond with lower levels of diversification, this result indicates that the farms with the least amount of diversification were the most resilient. The other two buffering capabilities were not statistically significant. The negative sign on the debt to asset ratio coefficient would indicate that lower debt to asset ratios correspond with higher levels of resilience. The positive coefficient estimate for the crop inventory variable would indicate the higher levels of crop inventory values prior to the shock corresponded with higher levels of resilience.

The coefficient estimates for the age and squared age variables were similar to the results shown in Table 6.7. The age variable is negative and significant, with a marginal effect that indicates a one percent increase in the age of the farmer corresponded with a 13.2% decrease in the resilience index value. However, the squared age coefficient estimate was positive, with a marginal effect that indicates a one percent increase in the squared age of the farmer corresponded with a 6.7% increase in the resilience index value. The squared value of the acres operated was also significant and negative. The marginal effect indicates that a one percent increase in the squared value of the acres caused a 0.1% decrease in the resilience index value. This would mean that when farms get very large they actually have lower levels of resilience.

The northwest regional variable was negative, though statistically insignificant. The southwest variable was positive and statistically significant. The marginal effect for this variable indicates that farms in the southwest region during the first shock were generally more resilient than farms in the southeast. The northcentral and southcentral regional coefficient estimates were positive, though statistically insignificant. And finally the northeast regional coefficient estimate was positive and significant, indicating that farms in the northeast were more resilient during the first shock period than farms in the southeast.

Table 6.8: Fractional response logit model estimates for resilient farms from the first shock period; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	-0.834	1.041	-0.800	0.423	-2.874	1.205	-0.001	-0.830
DVA_i	1.829	0.701	2.610	0.009	0.456	3.202	0.004	2.230
$CropInv_i$	0.000	0.000	0.110	0.910	0.000	0.000	0.000	0.110
$\Delta RDiv_i$	0.017	0.054	0.310	0.755	-0.088	0.122	0.000	-0.310
$\Delta ADiv_i$	-0.753	1.547	-0.490	0.626	-3.785	2.279	0.000	0.260
ΔOER_i	-2.241	0.870	-2.570	0.010	-3.947	-0.535	0.001	1.990
Age_i	-0.500	0.181	-2.760	0.006	-0.855	-0.144	-0.132	-2.550
Age_i^2	0.005	0.002	2.680	0.007	0.001	0.009	0.067	2.500
$Acre^2$	0.000	0.000	-1.730	0.084	0.000	0.000	-0.001	-1.680
NW	-0.062	0.520	-0.120	0.905	-1.082	0.958	0.000	0.010
SW	1.068	0.329	3.250	0.001	0.424	1.712	0.009	4.910
NC	0.511	0.442	1.160	0.247	-0.355	1.377	0.003	0.860
SC	0.259	0.405	0.640	0.522	-0.534	1.052	0.002	0.340
NE	0.676	0.351	1.930	0.054	-0.012	1.365	0.005	2.220
$Constant$	5.854	4.246	1.380	0.168	-2.469	14.176	0.005	10.47

The results from estimating equation (18) using only observations from the second shock period are shown in Table 6.9. All of the buffering capabilities variables were statistically significant. The marginal effect for the debt to asset ratio indicated that a one percent increase in the debt to asset ratio corresponded with a 0.1% decrease in the resilience index value. The diversification of acres' marginal effect indicated that a one percent increase in the diversification index value corresponded with a 0.3% increase in resilience index values for resilient farms. Finally, a one percent increase in the average value of crop inventories for the three years prior to the shock corresponded with a 0.1% decrease in the resilience index value.

The change in revenue diversification adaptive capability variable was negative and significant. The marginal effect indicates, however, that for a one percent increase in the revenue diversification increase, there was less than a 0.1% change in the resilience index value. The change in acre diversification adaptive capability variable was positive, although not statistically significant. The final adaptive capability variable, the change in the operating expense ratio, was statistically significant and negative. The marginal effect indicates that a one percent decrease in the operating expense ratio corresponded with a 0.1% increase in the resilience index value.

The coefficient estimates for the age and age squared variables were again significant, and again the signs were opposite. The marginal effect for the age variable indicates that a one percent increase in age corresponded with a 3.3% decrease in the resilience index value, whereas the age squared corresponded with a 1.6% increase in resilience. Out of the regional variables, only the northeast was not significant. All of the other four regions also had positive coefficient estimates and marginal effects, indicating that the southeast region was less resilient during the second shock period.

Table 6.9: Fractional response logit model estimates for resilient farms from the second shock period; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	-0.369	0.239	-1.540	0.123	-0.837	0.099	-0.001	-1.580
DVA_i	1.013	0.501	2.020	0.043	0.031	1.995	0.003	1.900
$CropInv_i$	0.000	0.000	-2.930	0.003	0.000	0.000	-0.001	-3.280
$\Delta RDiv_i$	-1.251	0.291	-4.290	0.000	-1.822	-0.680	0.000	-0.390
$\Delta ADiv_i$	1.214	0.773	1.570	0.117	-0.302	2.729	0.000	-2.940
ΔOER_i	-2.912	0.813	-3.580	0.000	-4.506	-1.319	-0.001	-4.430
Age_i	-0.083	0.048	-1.740	0.082	-0.177	0.011	-0.033	-1.710
Age_i^2	0.001	0.000	1.570	0.117	0.000	0.002	0.016	1.510
$Acre^2$	0.000	0.000	0.920	0.357	0.000	0.000	0.000	0.880
NW	0.674	0.307	2.200	0.028	0.073	1.275	0.007	2.770
SW	0.518	0.273	1.900	0.058	-0.017	1.053	0.005	2.380
NC	0.411	0.222	1.850	0.064	-0.024	0.846	0.004	2.560
SC	0.389	0.185	2.100	0.035	0.027	0.751	0.003	3.600
NE	0.013	0.212	0.060	0.950	-0.402	0.428	0.000	0.000
$Constant$	-2.963	1.029	-2.880	0.004	-4.980	-0.946	0.008	16.010

In order to test the null hypothesis, $H1_0$, a Wald-type test for nonlinear constraints was performed using Stata for all three of the model specifications discussed above. To implement this test, the combined effect of the three buffering capabilities was specified as being equal to the combined effects of the three adaptive capabilities, as shown below in equation (27). The results for each of the three model specifications are listed under equation (27). The results from Tables 6.7 through 6.9 all indicate that the null hypothesis cannot be rejected, and the combined effects of buffering capabilities on resilience are not proven to be unequal to the combined effects of the adaptive capabilities on resilience. This does not support the hypothesis that buffering capabilities have an overall greater impact on resilience when the farm is specified as being resilient.

$$(DAR_i) * (DVA_i) * (CropInv_i) = (\Delta RDiv_i) * (\Delta ADiv_i) * (\Delta OER_i) \qquad (27)$$

Table 6.7: Wald Test: $chi^2 = 0.27$, and Prob $> chi^2 = 0.6009$

Table 6.8: Wald Test: $chi^2 = 0.19$, and Prob $> chi^2 = 0.6659$

Table 6.9: Wald Test: $chi^2 = 2.06$, and Prob $> chi^2 = 0.1515$

In order to test the second hypothesis, a second fractional response logit model was estimated as shown below in equation (28). Equation (28) states that the model was estimated for the farms which had a resilience index value of zero, which were also the farms that were classified as being not resilient. In order to estimate the fractional response logit model for these observations, the resilience index values that were computed for these farms prior to imposing the zero-value condition were used as the dependent variables.

$$R_i = fn([B_i], [A_i], [X_i]), \ \forall\, R_i = 0 \qquad (28)$$

The results from estimating the model defined in equation (26) are shown in Table 6.10 below. The only buffering capability variable that was significant was the average level of acreage diversification for the three years prior to the shock. The marginal effect from this variable indicates that a one percent increase in the acreage diversification will cause a 0.8% increase in the resilience index value. This result is comparable to the results shown in Table 6.7 for the same buffering capability. Again this indicates that lower levels of diversification prior to the shock caused higher resilience. The sign on the debt to asset ratio variable was positive indicating that higher levels of debt to asset ratios cause higher levels of resilience. This result is counter to the predictions; however, this variable was also statistically insignificant. The average value of crop inventories for the three years prior to the shock was also statistically insignificant, and was negative.

All of the coefficient estimates for the adaptive capabilities were negative, however they were also not statistically significant. Although the coefficient estimate of the revenue diversification variable had a z-score of -1.82, the marginal effect was positive and had a z-score of only 0.810. Also statistically insignificant were the age, squared age, and squared acres variables. The northeast region was estimated to be significantly less resilient than the southeastern region, however none of the other regional variables were significant. Finally, the time control variable was negative and statistically significant. This indicates that farms in the second shock period were significantly more resilient than farms in the first shock period. In order to better account for this difference in time periods, two additional models were estimated and their results are shown in tables 6.11 and 6.12.

Table 6.10 Fractional response logit model estimates for not-resilient farms from both shock periods; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	0.703	0.602	1.170	0.243	-0.477	1.883	0.002	0.950
DVA_i	1.684	0.785	2.140	0.032	0.145	3.223	0.008	1.870
$CropInv_i$	0.000	0.000	-0.010	0.990	0.000	0.000	0.000	-0.010
$\Delta RDiv_i$	-1.451	0.795	-1.820	0.068	-3.010	0.108	0.001	0.810
$\Delta ADiv_i$	-1.785	3.057	-0.580	0.559	-7.777	4.208	0.001	0.470
ΔOER_i	-0.905	0.885	-1.020	0.307	-2.639	0.830	0.000	-1.020
Age_i	0.007	0.102	0.070	0.942	-0.193	0.208	0.004	0.070
Age_i^2	0.000	0.001	0.070	0.944	-0.002	0.002	0.002	0.070
$Acre^2$	0.000	0.000	-0.940	0.347	0.000	0.000	-0.001	-0.940
NW	0.139	0.446	0.310	0.755	-0.735	1.013	0.001	0.090
SW	-0.778	1.157	-0.670	0.502	-3.046	1.490	-0.006	0.710
NC	-0.583	0.483	-1.210	0.228	-1.530	0.364	-0.005	1.570
SC	0.225	0.585	0.390	0.700	-0.921	1.371	0.003	0.140
NE	-0.657	0.407	-1.610	0.106	-1.456	0.141	-0.005	2.740
$Time$	-1.274	0.258	-4.930	0.000	-1.781	-0.768	-	-
$Constant$	-5.766	2.236	-2.580	0.010	-10.147	-1.384	0.010	5.71

The estimation results in Table 6.9 are from the model that was computed using only observations of non-resilient farms from the first shock period. The coefficient estimate for the debt to asset ratio buffering capability was statistically significant at the 99% confidence level. The marginal effect indicates that among non-resilient farms, a one percent increase in the debt to asset ratio buffering capability corresponded with a 0.1% decrease in the resilience index value. The coefficient estimate for the acre diversification index buffering capability variable was also significant at the 99% confidence level. The positive marginal effect indicates that one percent increase in the acre diversification index value corresponds with a 0.3% increase in the resilience index value. The coefficient estimate for the crop inventory buffering capability variable was not significant above the 90% confidence level, although it was positive indicating that larger values of crop inventories leading up to a shock correspond with higher resilience index values.

The coefficient estimate for the change in revenue diversification variable was not significant above the 90% confidence level, and the marginal impact was less than 0.1%. The coefficient estimate for the change in acre diversification adaptive capability variable was significant at the 95% confidence level and the sign was positive indicating that farms which became more specialized after the shock were more resilient. However, the marginal effect was significant and negative, and also less than 0.1%. The coefficient estimate for the operating expense ratio variable was not significant, and also had a marginal effect less than 0.1%.

The age and age squared variables were both statistically significant at the 95% confidence level. The marginal effect for the age variable indicates that a one percent increase in the age of the farmer corresponds with a 1.9% increase in the resilience index value. However, the marginal effect of the squared age of the farmer indicates that a one percent increase corresponds with a one percent decrease in the resilience index value. This would indicate that the oldest farmers are less resilient than those slightly younger than them. The coefficient estimate for the northwest regional variable was not significant above the 90% confidence level. However, the coefficient estimates for the other four regions were all positive and statistically significant at the 95% confidence level. This means that all of these regions were more resilient than the southeast region during the first shock.

Table 6.11 Fractional response logit model estimates for not-resilient farms from the 1980 shock period; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	-1.203	0.338	-3.560	0.000	-1.866	-0.540	-0.001	-3.710
DVA_i	1.712	0.399	4.290	0.000	0.929	2.494	0.003	3.520
$CropInv_i$	0.000	0.000	1.420	0.154	0.000	0.000	0.001	1.230
$\Delta RDiv_i$	0.179	0.598	0.300	0.764	-0.993	1.352	0.000	-0.330
$\Delta ADiv_i$	1.750	0.618	2.830	0.005	0.538	2.962	0.000	-3.900
ΔOER_i	0.125	0.546	0.230	0.819	-0.945	1.194	0.000	-0.230
Age_i	0.094	0.044	2.150	0.031	0.009	0.180	0.019	2.070
Age_i^2	-0.001	0.000	-2.240	0.025	-0.002	0.000	-0.010	-2.160
$Acre^2$	0.000	0.000	-0.800	0.425	0.000	0.000	-0.010	-0.790
NW	0.379	0.282	1.340	0.180	-0.175	0.933	0.002	1.270
SW	0.904	0.265	3.410	0.001	0.385	1.423	0.005	5.800
NC	0.493	0.213	2.320	0.020	0.076	0.910	0.002	3.320
SC	0.557	0.169	3.290	0.001	0.225	0.889	0.003	7.340
NE	0.666	0.230	2.900	0.004	0.215	1.117	0.004	4.540
$Constant$	-8.728	1.071	-8.150	0.000	-10.828	-6.628	0.005	10.470

The results shown in Table 6.10 are from the fractional response model that was estimated including only non-resilient observations from the second shock period. The coefficient estimate for the debt to asset ratio buffering capability variable was positive and not significant at the 90% confidence level. The coefficient estimate for the acre diversification buffering capability variable was positive and significant at the 90% level. The marginal effect indicates that a one percent increase in the acre diversification index value corresponds with a one percent increase in resilience. Finally, the coefficient for the crop inventory buffering capability variable was negative and not significant at the 90% level.

The coefficient estimate for the revenue diversification adaptive capability variable was negative and significant at the 90% confidence level, however, the marginal effect for this variable was positive and not significant at the 90% confidence level. The coefficient estimates for the other two adaptive capabilities variables were also statistically insignificant at the 90% confidence level. The coefficient estimate for the age variable was negative and significant at the 95% confidence level, however the marginal effects were not significant and were also positive. The age squared and acres squared variables were also insignificant at the 90% confidence level. Of the regional variable coefficient estimates, only the northeastern regional variable was significant at the 90% confidence level and was negative. However, the marginal effect estimates for the regional variables showed that the southwest, northcentral, and northeast regions were all statistically different from the southeast region, and all negative.

Table 6.12 Fractional response logit model estimates for not-resilient farms from the 1998 shock period; resilience index values against buffering capabilities, adaptive capabilities, and control variables

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.Interval]		Marginal Effects	Z / Chi-Sq
DAR_i	0.790	0.586	1.350	0.178	-0.359	1.939	0.004	1.040
DVA_i	1.587	0.923	1.720	0.085	-0.221	3.396	0.010	1.540
$CropInv_i$	0.000	0.000	-0.430	0.667	0.000	0.000	0.000	-0.450
$\Delta RDiv_i$	-1.722	0.994	-1.730	0.083	-3.671	0.226	0.002	0.790
$\Delta ADiv_i$	-2.280	3.570	-0.640	0.523	-9.277	4.717	0.002	0.490
ΔOER_i	-1.296	1.078	-1.200	0.229	-3.409	0.817	-0.001	-1.260
Age_i	-5.733	2.505	-2.290	0.022	-10.644	-0.823	0.006	0.090
Age_i^2	0.000	0.001	0.050	0.962	-0.002	0.002	0.002	0.050
$Acre^2$	0.000	0.000	-0.910	0.360	0.000	0.000	-0.001	-0.920
NW	0.258	0.399	0.650	0.518	-0.525	1.041	0.004	0.360
SW	-1.506	1.862	-0.810	0.419	-5.156	2.144	-0.011	1.680
NC	-0.734	0.532	-1.380	0.168	-1.777	0.310	-0.007	2.010
SC	0.195	0.640	0.310	0.760	-1.059	1.450	0.003	0.090
NE	-0.878	0.372	-2.360	0.018	-1.608	-0.148	-0.008	4.930
$Constant$	-2.963	1.029	-2.880	0.004	-4.980	-0.946	0.013	5.010

In order to test the null hypothesis, $H2_0$, a Wald-type test for nonlinear constraints was again performed using Stata for all three of the model specifications discussed above. To implement this test, the combined effect of the three buffering capabilities was specified as being equal to the combined effects of the three adaptive capabilities, as shown below in equation (29). The results for each of the three model specifications are listed under equation (29).

$$(DAR_i) * (DVA_i) * (CropInv_i) = (\Delta RDiv_i) * (\Delta ADiv_i) * (\Delta OER_i) \qquad (29)$$

Table 6.10: Wald Test: $chi^2 = 0.13$, and Prob $> chi^2 = 0.7170$

Table 6.11: Wald Test: $chi^2 = 0.02$, and Prob $> chi^2 = 0.8776$

Table 6.12: Wald Test: $chi^2 = 0.18$, and Prob $> chi^2 = 0.6743$

In order to test the null hypothesis, $H3_0$, a comparative analysis was conducted with the results of the six models that were estimated above. In addition, the buffering and adaptive capabilities from the resilient farms were compared to those of the non-resilient farms. For each of the six fractional response logistic model specifications that were estimated, the combined marginal effects of the buffering capabilities were larger than the marginal effects of the adaptive capabilities (Table 6.11). This result supports both of the null hypotheses, $H1_0$ and $H2_0$, that buffering capabilities have a stronger impact on resilience than adaptive capabilities.

The results in Table 6.11 also indicate that the marginal effects for the debt to asset ratio and acre diversification buffering capability variables were slightly stronger for the non-resilient farms as compared to the resilient farms. The resilient farmers, however, had slightly greater marginal impacts from the crop inventory buffering capability variable as compared to the non-resilient farms. The marginal effects from the revenue and acre diversification adaptive capabilities for the non-resilient farms were slightly greater than those of the resilient farms, however this was the opposite for the operating expense ratio adaptive capability variable.

Table 6.13: Estimated marginal effects for buffering and adaptive capabilities from the six models that were estimated

		DAR_i	DVA_i	$CropInv_i$	$\Delta RDiv_i$	$\Delta ADiv_i$	ΔOER_i
Resilient	Combined	-0.001	0.003	-0.001	0	0	0
	1980	-0.001	0.004	0	0	0	0.001
	1998	-0.001	0.003	-0.001	0	0	-0.001
Non-Resilient	Combined	0.002	0.008	0	0.001	0.001	0
	1980	-0.001	0.003	0.001	0	0	0
	1998	0.004	0.01	0	0.002	0.002	-0.001

Table 6.12 shows the average values of the buffering capabilities and adaptive capabilities for resilient and non-resilient farms for both shock periods combined, as well as, for observations from the first shock period (1980) and observations from the second shock period (1998). The resilient farms had a slightly higher average level of debt to asset ratio leading up to the shock, as compared to the non-resilient farms. In addition, the resilient farms had slightly lower average values of the acre diversification index, indicating these farms were on average slightly more diversified. Also, resilient farms in the first shock period had slightly lower average values of crop inventories in the three years prior to the shock as compared to non-resilient farms. On the other hand, resilient farms had slightly higher values of this variable during the second shock period as compared to non-resilient farms.

Resilient farms in the first shock period had a larger average change in the revenue diversification index value as compared to non-resilient farms in the first shock period. For resilient farms the average change in the revenue diversification index value was -0.2694, which meant that resilient farms on average increased their level of revenue diversification by more than the average of the resilient farms (which had a change of only -0.0255). Similarly, the average value for resilient farms in the second shock period was also larger than the average value of non-resilient farms in the second shock period. On the other hand, resilient farms had lower average values of the change in the acre diversification index values, indicating that the resilient farms had less of a change in diversification, although overall the change was to become slightly more diversified (evidenced by the negative signs). Finally, the resilient farms in the first shock period had a nearly equal average value of the change in operating expense ratios (-0.087) as compared to the non-resilient farms (-0.083). However, in the second shock period, the resilient farms had a smaller change in this variable as compared to the non-resilient farms.

Table 6.14: Average values of buffering and adaptive capabilities for resilient and non-resilient farms for both shock periods, the first shock period (1980), and the second shock period (1998)

		DAR_i	DVA_i	$CropInv_i$	$\Delta RDiv_i$	$\Delta ADiv_i$	ΔOER_i
Resilient	Combined	0.3074	0.3817	65328	-0.0236	-0.0089	0.0159
	1980	0.2912	0.4042	53522	-0.2694	-0.0092	-0.0875
	1998	0.3129	0.3742	69263	0.0584	-0.0088	0.0504
Non-Resilient	Combined	0.2904	0.4013	63989	-0.0132	-0.0265	0.0277
	1980	0.2763	0.4169	56840	-0.0255	-0.0325	-0.0833
	1998	0.2972	0.3939	67402	-0.0073	-0.0236	0.0807

As a result of this comparative analysis the null hypothesis, $H3_0$, cannot be rejected. Although the buffering capabilities for resilient farms had higher marginal effects and larger average values in some cases, it was not strictly the case. In addition, the largest difference in buffering and adaptive capabilities variables was for the change in revenue diversification adaptive capability, between resilient and non-resilient farms in the first shock period. The results indicate that the ability to mobilize resources to generate revenue from a more diverse group of sources appears to have driven the main difference between resilient and non-resilient farms. Additionally, there was a clear difference between the change in acre diversification adaptive capability variable for resilient farms and non-resilient farms. On average, the non-resilient farms had larger increase in acre diversification following the initial impact of the two shocks, compared to the resilient farms.

Chapter 7: Conclusion and discussion of results

The purpose of this study was to examine the resilience of Kansas crop farms when faced with periods of economic shock. This was accomplished by first conducting a review of the literature concerned with system resilience in general, as well as, agricultural resilience specifically. It was determined through this review of the literature that empirical studies of farm resilience have been relatively underdeveloped. The contribution of this research was therefore to conduct an empirical analysis of farm resilience based on existing theories in system and agricultural resilience. A conceptual model was developed to apply an existing resilience measure, the resilience triangle, to a production agriculture setting. The resilience triangle has been applied previously to measure the resilience of hospital infrastructures following earthquakes, the resilience of automobile supply chains, and agricultural supply chains. This study is the first application of the resilience triangle method at the individual farm level.

In addition to the application of the resilience triangle method, a model of farm resilience was developed based on the existing literature in agricultural resilience. In this model, farm resilience is driven by three defining capabilities: buffering capability, adaptive capability, and transformative capability. Variables were chosen to represent these three capabilities, along with several farm-specific variables that were also thought to impact resilience. To conclude the conceptual framework, three hypotheses were made concerning the impact of the resilience capabilities on overall farm resilience.

The data for this analysis was obtained from the Kansas Farm Management Association (KFMA). Based on the literature review and the conceptual framework, resilience triangle areas were computed for individual farms during two distinct periods of economic shock, 1980 and

1998. An index of farm resilience was generated from the resilience triangle areas, which were then used as dependent variables in the econometric analysis.

For the econometric analysis, a fractional response logit model was estimated because the resilience index values ranged between zero and one. When dependent variables are restricted like this, standard OLS estimation would not produce reliable results. The fractional response model was developed by researchers in order to be able to produce robust coefficient estimates in the cases when dependent variables are restricted to range between zero and one. The estimated coefficients from this type of estimation cannot be easily interpreted, however, this was easily remedied by taking the marginal effects.

The results of the analysis indicated that there are differences in the ways that buffering and adaptive capabilities impact overall farm resilience. In both shock periods, the marginal effects of the buffering capabilities were generally larger and more statistically significant than those of the adaptive capabilities. However, when conducting a Wald test of significance, the null hypotheses were not rejected. There was not a statistically significant difference in the impacts of buffering and adaptive capabilities on resilience index values. Moreover, there were not conclusive findings that buffering capabilities were stronger among the resilient farms as compared to the non-resilient farms. These results indicate that farm resilience is driven by both buffering and adaptive capabilities jointly. Even though buffering capabilities are important at the outset of a shock, the farm will then need adaptive capabilities to recover from the initial impact of the shock.

The concept of system resilience is grounded in the philosophy that systems will always be vulnerable to unpredictable shocks. Rather than attempting to mitigate the potential impacts from specific sources of risk, system resilience is focused on preparing the system to buffer against any kind of shock and then have the adaptive capabilities to recover in the post-shock environment. Developing resilience is a continual process in which stakeholders are regularly evaluating their resource allocation decisions. Although there are more risk management tools available to farmers today than there have been in the past, there is still a need to improve upon the available options and create new ways of securing agricultural production into the future. The drop in average U.S. net farm income from 2014 through 2016 has indicated that current risk management options available to farmers have not fully mitigated the risks associated with farming. By applying system resilience theories to production agriculture, a new set of risk management tools becomes available to farmers and policy makers. By understanding the drivers of overall farm resilience, better decisions can be made and food production can become more secure.

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Appendix A – Causes of the Shocks

A.1 Causes of the first shock period

To look deeper into the changes in net farm income at the regional level during the first shock period, average nominal value of farm production is graphed in Figure A.1. There are clear differences across all regions for this variable, promoting the finding that the economic shock of the early 1980's was experienced differently across regions. In Figure 3.10, the average value of farm production in the southwest region is continually at the top of the group. This means that average per-farm value of farm production in southwest Kansas was higher than other regions in the 1980's. Farms in south central Kansas, on the other hand, typically experienced the lowest average levels of value of farm production throughout this period. Going from 1979 to 1980, average value of farm production dropped in all regions, however, from 1980 to 1981 average value of farm production decreased in the north central, northwest, and southwest regions, but increased in the south central, southeast, and northeast regions. Initially, after the shock occurred in 1980 and 1981, value of farm production in southwest and northwest Kansas recovered strongly. Later, in 1986, average value of farm production for northeast and southeast Kansas farms increased to a higher level, while average values remained lowest for north central and south central farms.

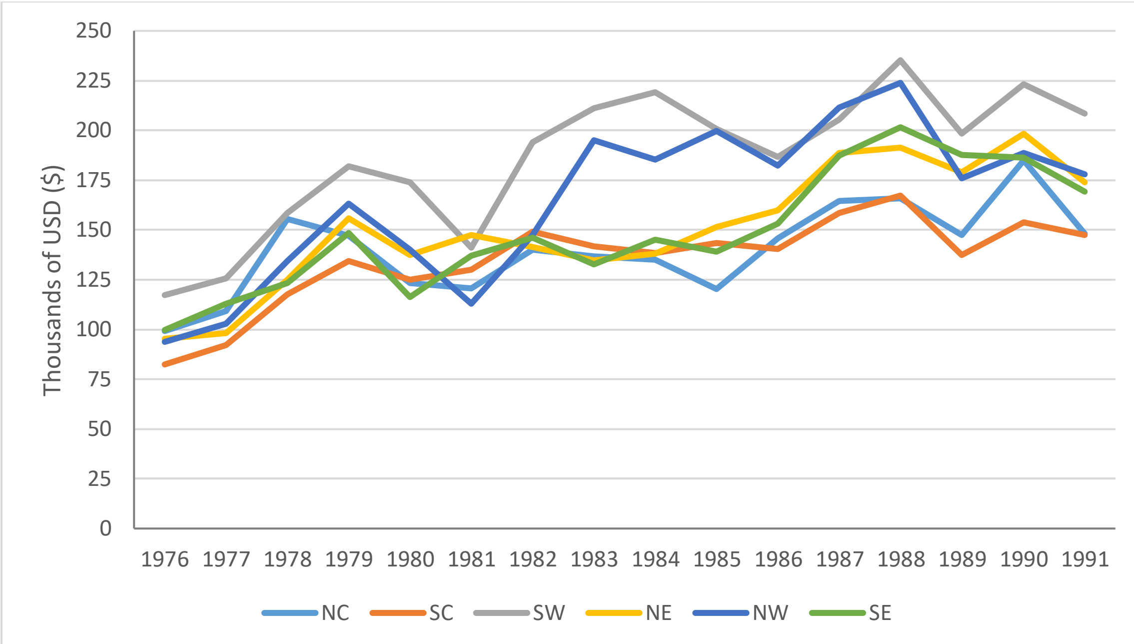

Figure A.1: Average nominal value of farm production by region, all KFMA farms (1976-1991)

The value of farm production, is calculated as cash income from crops and livestock, minus feed expense, plus changes in grain and livestock inventories, plus government payments. Thus, if the value of farm production were to decline, fluctuations in these variables would be observed. Interestingly, the average cash income earned per farm from grain crops, hay/forage crops, and cash crops for all KFMA farms between 1973 and 1991 remained relatively stable (Figure A.2). While there is some fluctuation in grain crop revenue, average levels were relatively stable in the 1979-1982 period when the dramatic decline in net farm income occurred. Average income from cash crops even increased during this period. This is an important finding because a major agricultural embargo against the former Soviet Union was enacted by president Jimmy Carter in 1980, which is often cited as being a major cause of the 1980's farm crisis. If this trade embargo did in fact impact the sales and exports of U.S. grain farmers, it does not appear to have done so among KFMA farmers (in terms of cash income earned from the sales of grains).

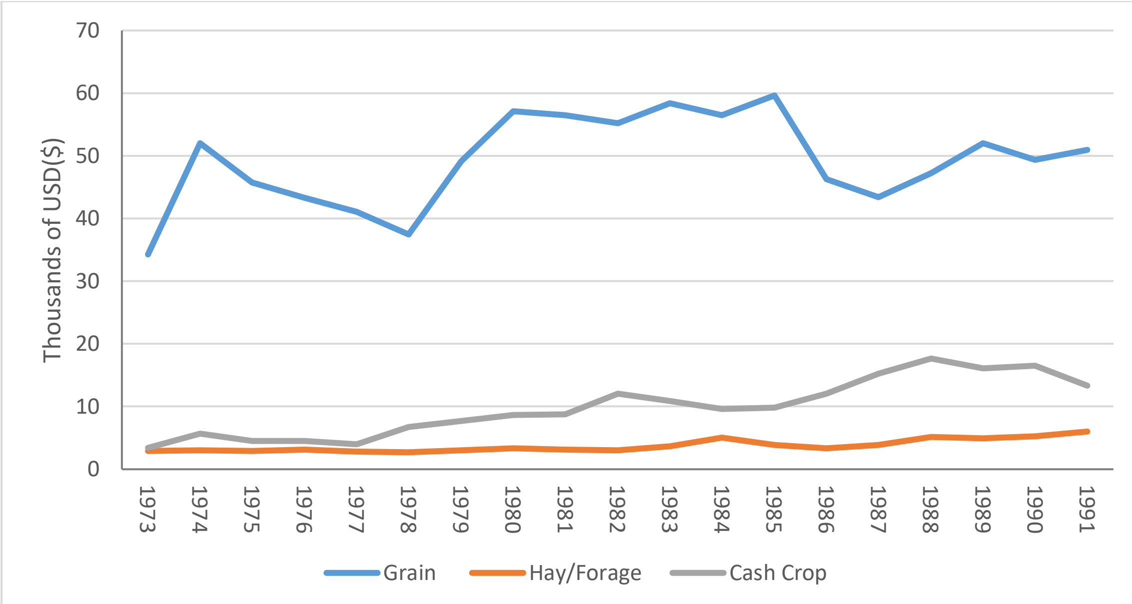

Figure A.2: Average income earned by KFMA farms from sales of crops (1973-1991)

The graph in Figure A.3 shows the average cash income earned by KFMA farms from the sales of grains (the major revenue generating crop in Kansas) in each of the six KFMA regions. Going from 1980 to 1981, cash income from grains did actually decline in the southwest, northwest, and northcentral regions. In the southeast, northeast, and southcentral regions the farms actually saw increases in grain crop income between the same two years. Because grain income earned dropped for the southwest and northwest regions, and these two regions also experienced the largest drops in value of farm production, it is possible that the economic shock (and perhaps the trade embargo) was felt the strongest in these regions.

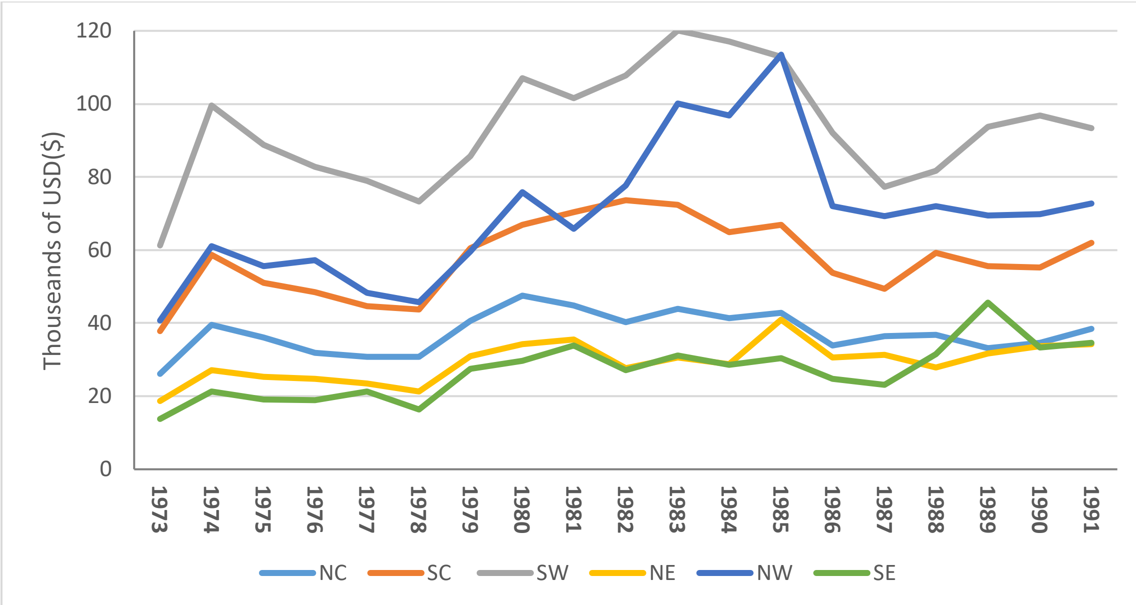

Figure A.3: Average income earned by KFMA farms from sales of grains, by region (1973-1991)

The value of farm production also contains changes in inventory and government payments. The average level of government payments for KFMA farmers between 1973 and 1991 is graphed by region in Figure A.4. From 1978 to 1980, average government payments per farm declined. This makes sense because at the same time, farm incomes were booming (hence not requiring supplemental financial support from the government). This is also indicative of the type of policy that prevailed at the time. Government aid was primarily offered to grain farmers in the years after the 1977 farm bill using two formats: (1) price supports and (2) income supports.

Under the price support system, farmers could utilize a loan/storage program that would take storage of crops in exchange for a loan. At the end of the loan life the farmer could either repay the loan and retain ownership of the commodity, or, forfeit the commodity in exchange for loan forgiveness. The program worked by setting a per-unit rate (or price) at which the government would pay for the commodity. The income support system, on the other hand, would provide farmers with direct payments equal to the difference between the current market price and the government established target price when market price dropped below the target price (or this would be the difference between market price and the established loan rate, whichever was smaller). This type of government agricultural support would have most likely benefitted larger farms over smaller farms because payments were based on absolute quantity produced.

The graph in Figure A.4 shows that a unanimous drop in government payments occurred in 1980, the year prior to the record-low net farm income in 1981. The two regions that experienced the largest drops in government payments were northwest and southwest Kansas (also the regions with the largest drop in cash income from sales of grains). These are also the two regions with the largest average farm size, and the two regions with the most amount of government support on average per farm both before and after the shock. Thus, again, the shock may have been felt more strongly in these regions.

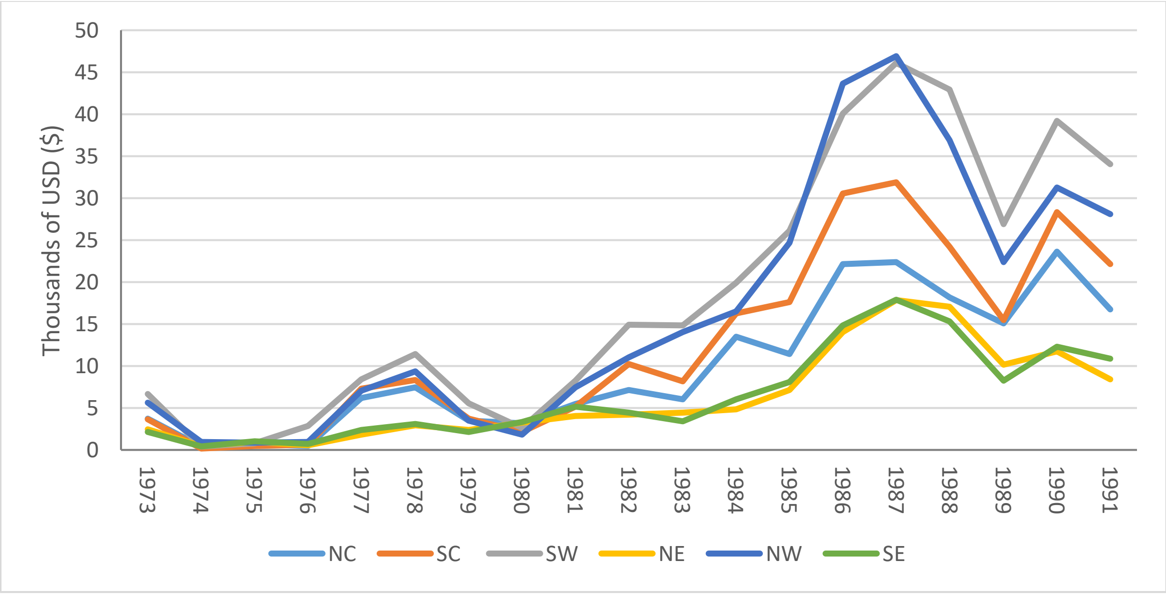

Figure A.4: Average annual government payments to KFMA farms, by region (1973-1991)

The final component of the value of farm production is the change in crop inventories. Figure A.5 graphs the changes in inventories of grain crops, cash crops, and hay crops for KFMA farms between 1976 and 1991. The greatest amount of fluctuation occurred within the grain crop inventory during this time period. Grain inventories were rising between 1976 and 1979, a result of strong production, advancements in machinery and efficiency, and strong demand for U.S. agricultural production. Then in 1980 and 1981 KFMA farms on average experienced significant declines in dollar values of their grain inventories. In particular, the average per-farm change in grain inventories in 1980, 1981, and 1982 were negative.

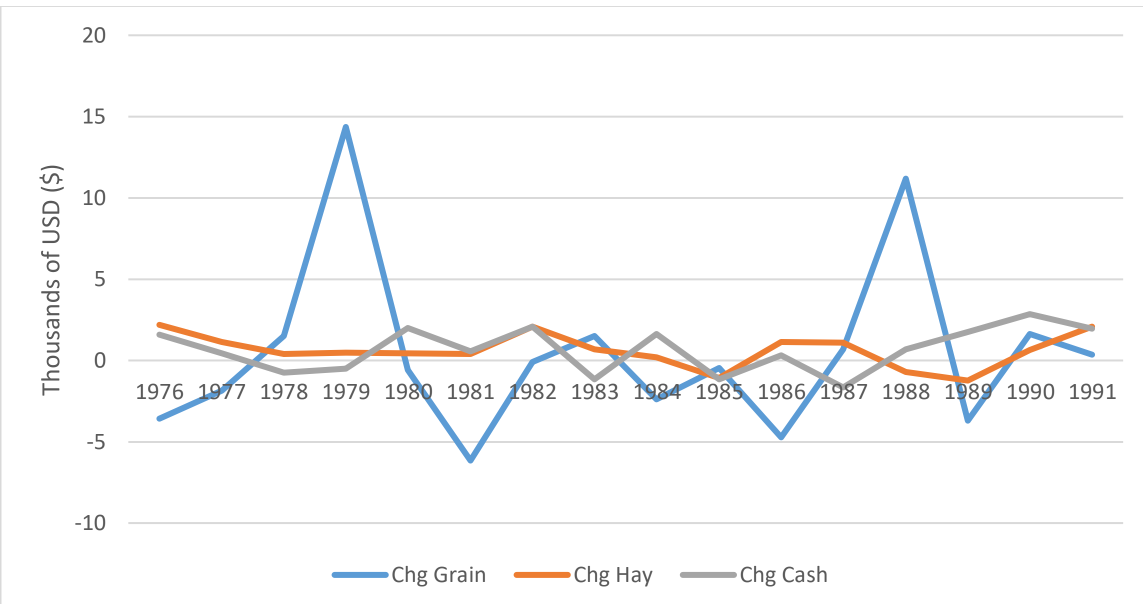

Figure A.5: Average dollar value change in crop inventories, all KFMA farms (1976-1991)

To summarize the changes in the *value of farm production* during the first shock period, sales of grains were relatively stable statewide during the 1980-1982 period. At the regional level, farms in the northwest and southwest Kansas did experience average declines in the cash sales of grains. Statewide, however, the average KFMA farm experienced significant declines in government support as well as negative changes in crop inventories.

Moving next to a discussion of average cash farm expenses during the first shock period, Figure A.1 revealed that there was not necessarily a sudden spike in nominal cash farm expenses. However, a gradual increase in cash farm expenses occurred in the years leading into 1981. For example, in 1976 the region with the highest average per-farm cash expenses was southwest Kansas (averaging $91,000 per farm). Farms in the south central region had the lowest average cash expense levels at $63,000. By 1981, the south central region still posted the lowest average cash farm expenses, however this had climbed to $109,000 per farm and farms in the southwest region had average cash farm expenses of $134,000. Thus, between 1976 and 1981, the gradual but powerful rise in cash expenses left farmers financially exposed when the shock hit in 1980 and 1981. Also worth noting is that the lowest cash farm expenses were typically experienced by farms in the eastern portion of the state and the highest expenses were typically seen in the western portion of the state. This was most likely due to farm size, but it is an important distinction consider.

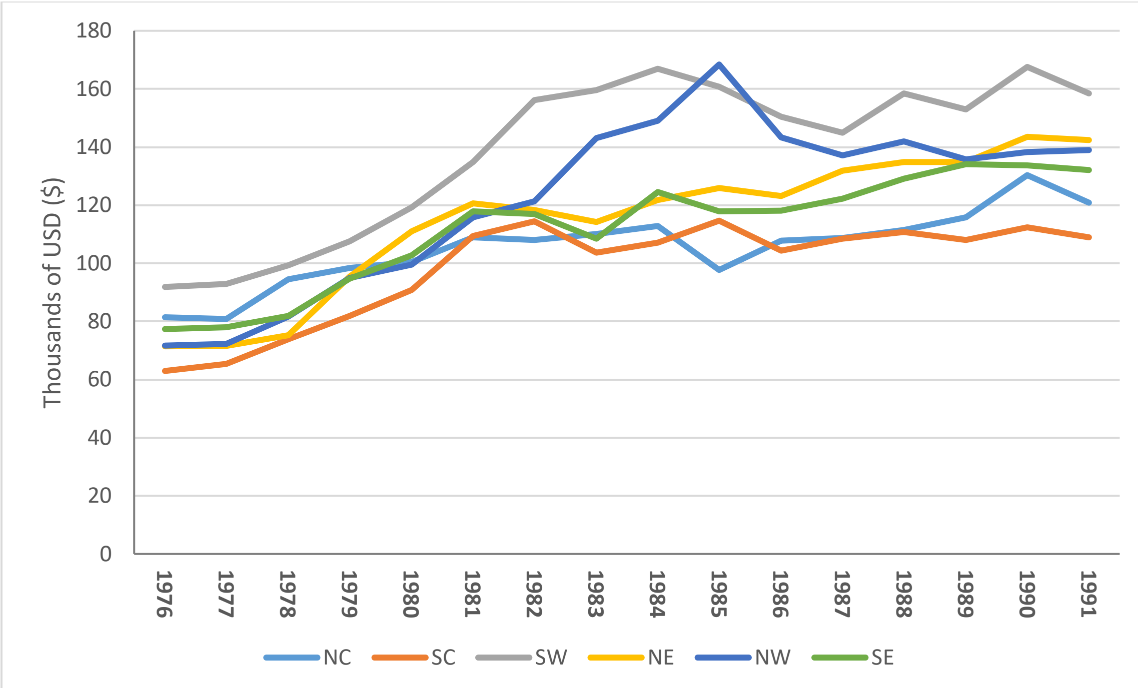

Figure A.6: Average nominal cash farm expenses by region, all KFMA farms (1976-1991)

The pronounced increase in average levels of nominal cash farm expenses between 1977 and 1981 was driven primarily by rapid increases in average levels of interest rates. In 1979 Paul Volcker became chairman of the Federal Reserve Bank and subsequently initiated an intense period of tight monetary policy as an attempt to regulate volatile inflation rates. The goal of the policy was eventually achieved, however interest rates increased drastically during this time period. Figure A.7 graphs the Federal Funds Rate (FFR) between 1974 and 1995. In 1981 the FFR reached levels as high as 19%, only dropping to pre-Volcker levels again in the early 1990's. Fluctuations in the Federal Funds Rate directly impact many interest rates throughout the economy, and interest rates in the agricultural community are traditionally not immune.

The impact of the interest rate spike on KFMA farms can clearly be seen in the graph in Figure A.8. The period with the highest payments was between 1981-1983, when farmers were paying on average more than $22,000 per year in interest payments. Farms in the southwest and northwest regions were most impacted in terms of total magnitudes of interest rate payments. In particular, a peak occurred in 1985 in northwest Kansas when farms on average were paying $35,000 per year on interest alone. This kind of spike in cash farm expenses will undoubtedly have put strain on famers' ability to effectively utilize resources, make allocation decisions, and continue to produce output. Across all regions, interest payments declined in the late 1980's and stabilized in the 1990's.

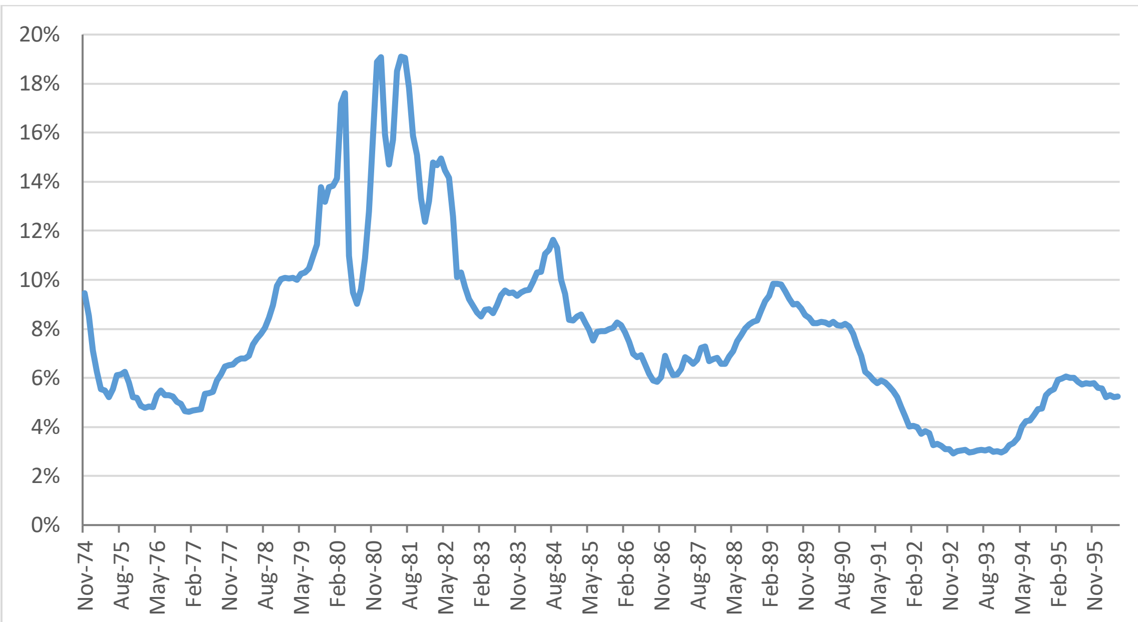

Figure A.7: Federal Funds Rate (1974-1995)

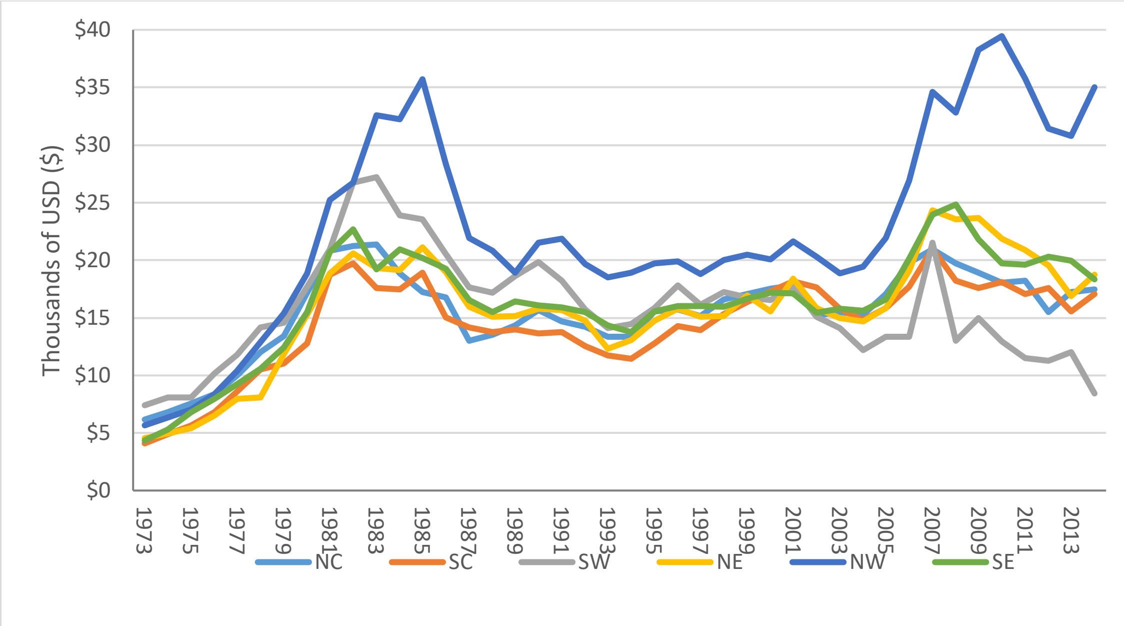

Figure A.8: Average nominal interest payments, all KFMA farms, by region (1973-2013)

It is important to also consider that higher interest payments alone would not cause a drop in net farm income because they could of course be matched with simultaneously high levels of farm revenues. Using leverage on a farm enterprise is fairly common in the U.S., and high levels of debt could also indicate high levels of lender confidence. Therefore, Figure A.9 shows average interest payments as a percentage of the average value of farm production for all KFMA farms. The graph shows that the average KFMA farmer was using 20% of value of farm production to service interest on debt in 1981. Thus, this large increase in the magnitude of interest payments was, in fact, not met by equally large increases in farm production value.

Regionally, Figure A.10 shows that again farms in the northwest of Kansas maintained the highest levels throughout the early 1980's. Thus, not only did northwest farms experience the highest per-farm interest payments, they also allocated the largest portion of farm production value towards interest payments. On the other hand, although farms in the southwest region had the second highest average interest payments per farm, they did not have the second highest percent of value of farm production going to pay interest. In fact, farms in this region had the lowest percentage in 1984, and remained near the bottom throughout the next two decades. This finding should provide a basis of comparison between two regions in Kansas.

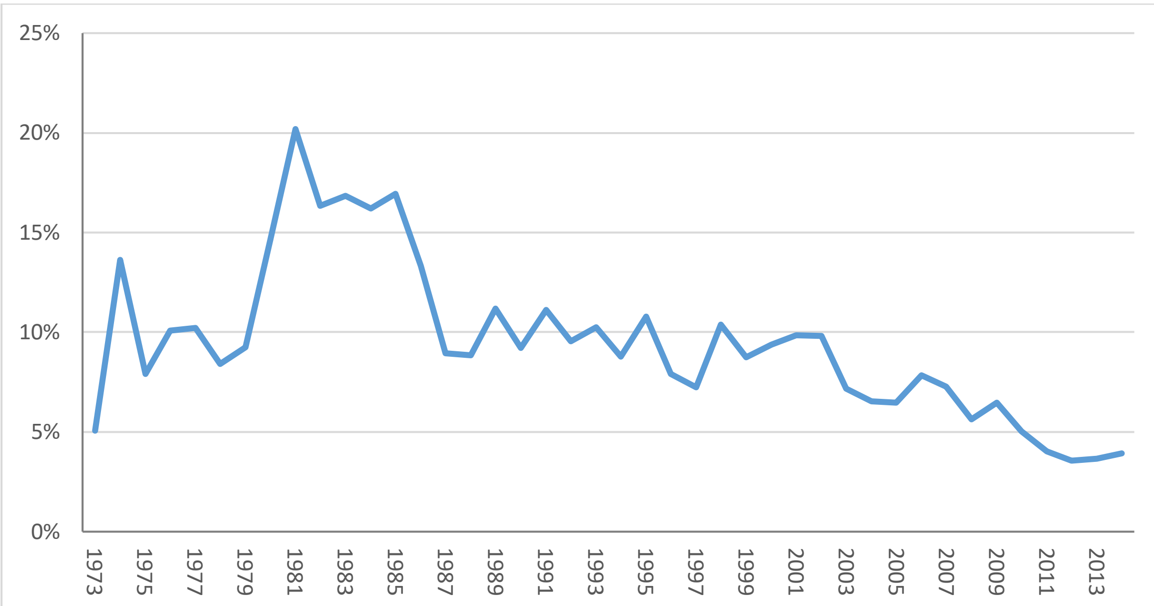

Figure A.9: Average interest payments as a percent of average value of farm production

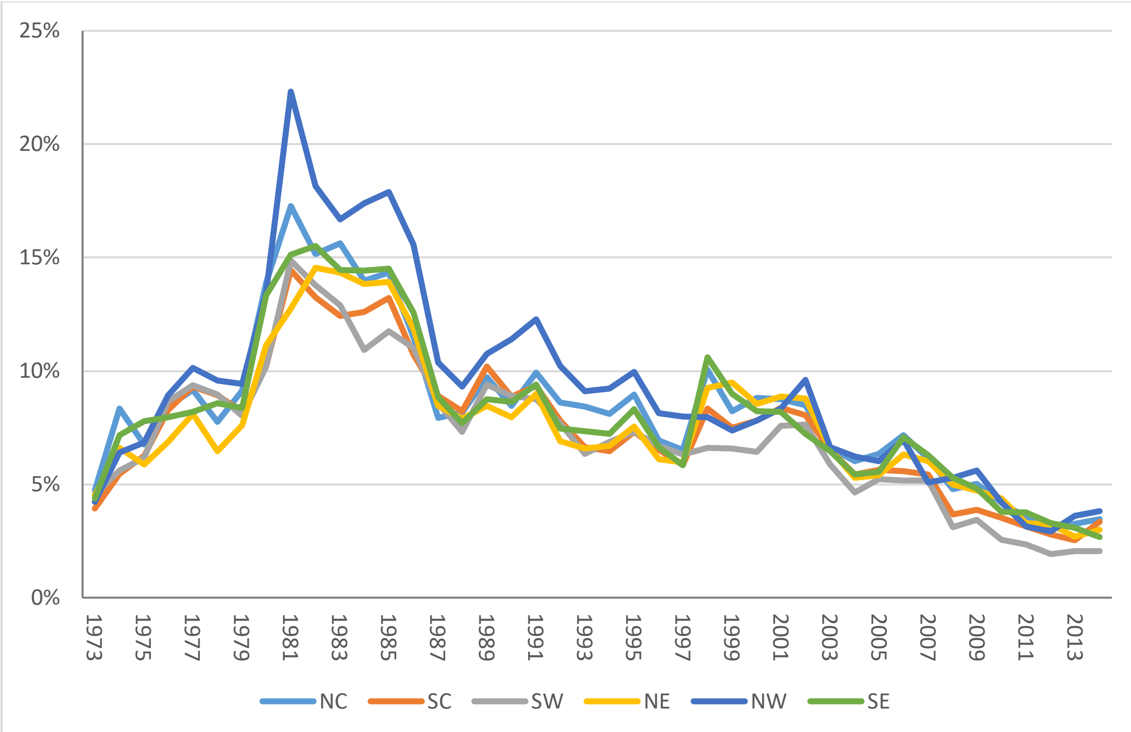

Figure A.10: Average interest payments over value of farm production for KFMA farms, by region (1973-2013)

A.2 Causes of the Second shock period

The graph in Figure A.11 shows average prices received by farmers in Kansas between 1976 and 2012 for corn, wheat, and sorghum. The price of sorghum in 1995 was $2.76 per bushel, and by 1998 it dropped to $1.62 per bushel (a 41% decline). Likewise, prices of corn and wheat began to decline in 1996. Corn went from $3.55 per bushel in 1996 and then dropped by 48% to $1.86 in 2000. Nominal prices of corn did not go above $3.00 per bushel again until 2007. Finally, wheat price received by Kansas famers averaged $4.77 in 1996 and then dropped by 46% to bottom out in 2000 at $2.57 a bushel.

While declining prices will impact revenues of farmers, the magnitude of the impact can vary depending on a number of factors. For example, if farmers have increased production levels in response to rising prices, this must also mean that expenses have increased. Then, when a price drop happens, the farmer may find it difficult to repay higher costs that have already been accrued. In fact, this appears to have happened to KFMA farmers during this time period, as can be seen in Figures 3.20 and 3.21. Leading up to the price shock of 1997-1998, Figure A.11 shows that prices were increasing for all three crops. Wheat prices increased 74% between 1991 and 1996, while corn price increased 52% over the same period. Likewise, sorghum prices increased 33% between 1991 and 1995.

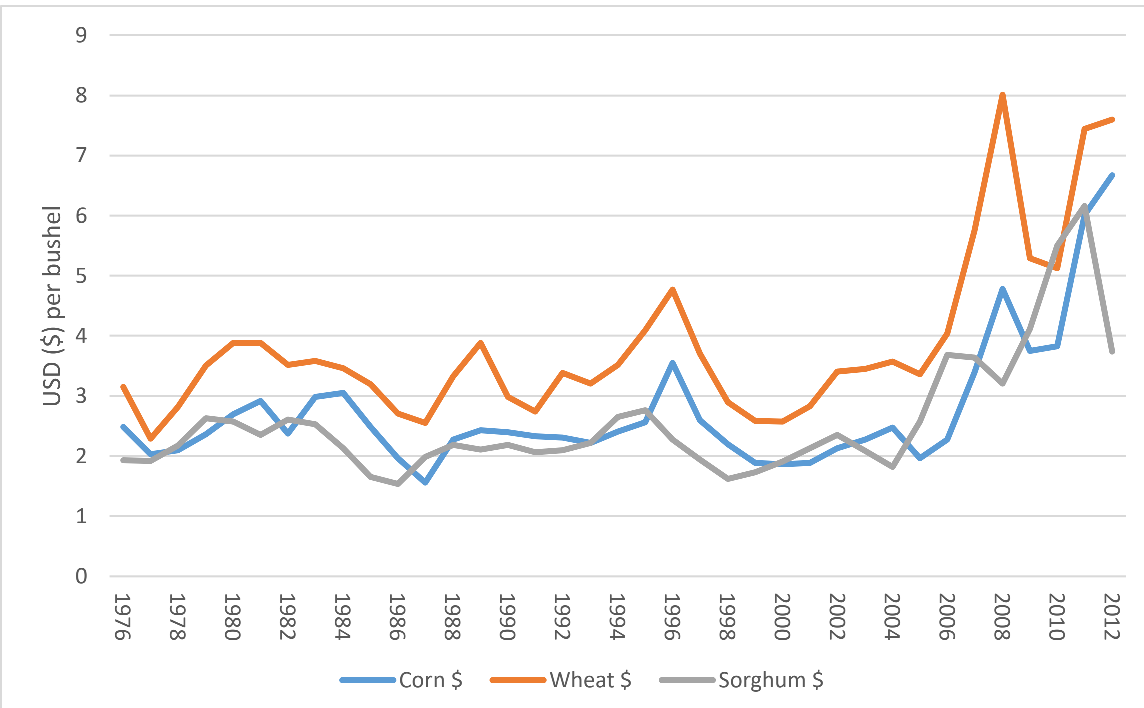

Figure A.11: Average price received by Kansas farmers for corn, wheat, & sorghum (1976-2012)

The increase in cash expenditures appear to be directly related to an increase in production of all three grain crops. The largest increases in expenses were seen in the western portions of the state, and were primarily driven by greater payments towards seed, fertilizer, and herbicide/insecticide. Figure A.12 shows that production of corn and sorghum increased rather dramatically between 1995 and 1996, and wheat increased between 1996 and 1997. The drop in wheat production between 1994 and 1996 is actually explained by increased wheat acreage abandonment rates in 1995 and 1996 (Figure 3.21). Without those poor harvest years, production of wheat would have most likely increased along with corn and sorghum. Hence, overall attempted production increased just prior to the income shock of 1998, meaning investment in crop production increased. So, when prices dropped (as a result of increased domestic supply, global supply, and slight downturns in demand due to the Asian financial crisis), the negative hit to value of farm production was significantly more pronounced.

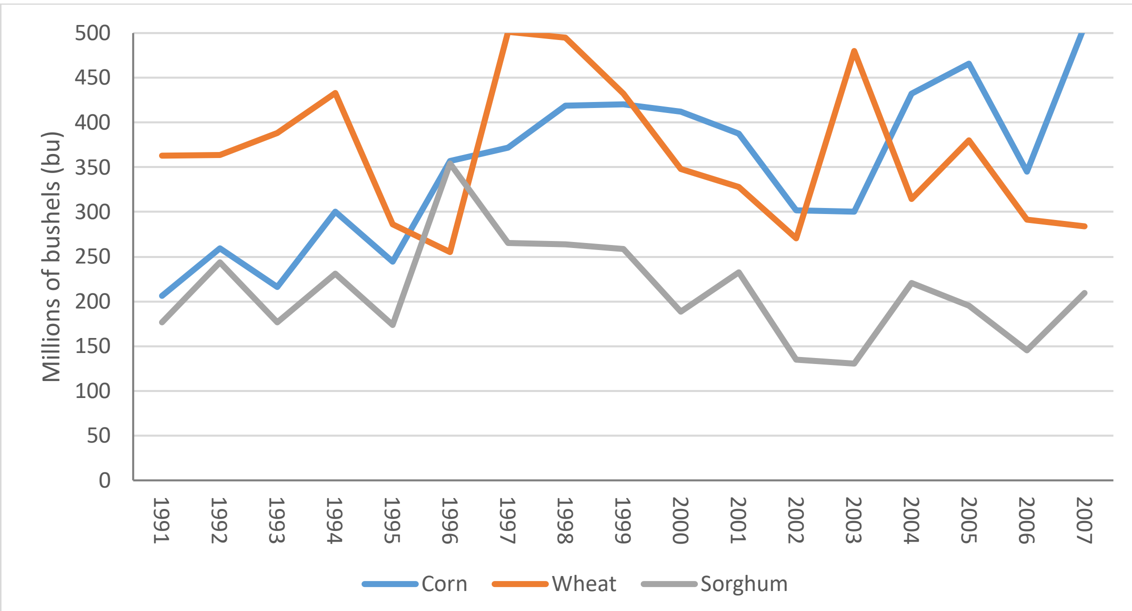

Figure A.12: Total production of corn, wheat, & sorghum, all Kansas farms (1991-2007)
Source: USDA Quick Stats

To summarize, the second shock period was felt on average across all farms in the KFMA database. The shock was a result of a steady increase in production over several seasons followed by a sudden drop in commodity prices. This drop in prices caused the value of farm production to diminish quite rapidly in 1998, thus causing a drop in average real net farm income.

The second shock period occurred when net farm income dropped by 71% from 1997 to 1998. As shown previously, this drop in net farm income was caused by a major drop in the value of farm production. To get a better understanding of this shock, average nominal net farm income by region is graphed in Figure 3.10. This graph illustrates that the drop in net farm income during the second shock was not felt equally across all regions. Farms in the southeastern part of Kansas were impacted most negatively (96% drop in net farm income), followed second by farms in the northeast, north central, and south central regions (drops of 75%, 73%, and 71% respectively). The least impacted farms during this economic shock were in the southwest and northwest portions of the state (30% drop in net farm income for southwest and 60% drop in net farm income for northwest).

Given that this drop in net farm income was caused entirely by a drop in value of farm production, potential causes are examined. Again, value of farm production is computed using sales of crops and livestock, government payments, changes in inventories, and changes in accounts receivable. After examining each of these components, it was determined that the decline in value of farm production came primarily from major price drops for corn, wheat, and sorghum unanimously in the 1996-2007 period of time.