Farm resilience: evidence from Kansas

by

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Abstract

The purpose of this study is to build on the findings of Lindbloom (2018) on the effect of diversification on farm resilience and expand the literature in two main ways. First, this study examines farm resilience over a larger time period including the most recent shocks related to the farm income decline of 2015 and the US-China trade war of 2018. Second, the empirical model is enhanced to include adaptive capabilities. Specific objectives include (i) measuring the resilience of Kansas agricultural producers at the individual farm level during four shocks in the 1980-2021 period, and (ii) estimating an enhanced empirical model to gain more insights on the effect of farm level resources and capabilities on a farm's ability to withstand (buffering) and restructure (adaptive) during the exogenous shocks. The objectives will be achieved by adopting and extending the conceptual and analytical frameworks from Lindbloom (2018).

The data for this research was obtained from the Kansas Farm Management Association (KFMA), which contains detailed farm-level financial and production information for farms in Kansas between 1973 and 2021. Resilience index values have been computed at the individual farm level for four shock periods using a similar approach as Lindbloom (2018). Regression analyses are conducted by conducting a fractional logit model.

The main findings of the study indicate that the buffering capabilities identified in Lindbloom (2018) are generalizable across an expanded range of shocks. The results also indicate that in addition to diversification, crop inventory, and debt-to-asset ratio, the depreciation ratio serves as a buffering capability for the shocks during the period analyzed. Lastly, the results indicate that the presence of a non-linear relationship between a number of farm characteristics and farm resilience, implying that certain resources and capabilities can serve as buffering and adaptive capabilities up to a specific threshold beyond which their impact

on resilience turns negative. This study extends the existing literature on farm resilience and provides an enhanced conceptual and analytical platform for future studies over extended time periods including COVID-19 and Russia-Ukraine conflict related shocks.

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Chapter 1 - Introduction

Risk and uncertainty are inexorable facts of life for agricultural producers. Over time, various risk management techniques have been developed that help farms and farming businesses to manage the impacts of the shocks caused by specific sources of risk. Unfortunately, currently available risk management methods lack the ability to cope comprehensively with uncertainty. Over the last four decades, the agricultural community has witnessed a number of unprecedented shocks ranging from the financial farm crisis in the 1980s to the U.S. farm trade balance decline in 1998 to the price fluctuation in 2015 to the US-China trade war in 2018. While traditional agricultural risk management tools help manage risk, they are limited in their capacity to improve agricultural producers' resilience to uncertainties brought by unanticipated shocks. The concept of system resilience has emerged to complement conventional risk management options.

Literature defines system resilience as "… the capacity of a system to anticipate, adapt, and reorganize itself under conditions of adversity in ways that promote and sustain its successful functioning" (Ungar, 2018). Based on this definition of resilience, agricultural resilience may be described as the producers' capacity to recover (go back to its pre-shock or improved state) after experiencing an unanticipated economic or environmental shock. Considering that an agricultural production unit (a farm) is a socio-ecological system, the recent system resilience methodologies that have been used in this research can provide insights on strategies for helping farms to face unexpected shocks.

Lindbloom (2018) was the first to attempt to measure resilience at the individual farm level. In his conceptual model, farm resilience is affected by three types of capabilities: buffering, adaptive, and transformative. Where buffering capability is defined as the ability of the farm to withstanding the impact of the shock, adaptive capability as the farm's ability to adjust and recover from the initial impact of the shock, and lastly, the transformative capability is the ability to undergo radical change (transformation) and recover stronger (Darnhofer, 2014).

Lindbloom (2018), examined the resilience of Kansas farms that faced various shocks during the 1973 - 2014 time period. The findings indicated that farm diversification, debt-to-asset ratio, and crop inventory served as buffering capabilities for the shocks included in the period analyzed. The results provided limited evidence for adaptive capabilities, while the transformative capabilities were excluded from the scope of the empirical model. As a result, several important questions remain unanswered. First, what farm characteristics constitute adaptive and transformative capabilities and second, how effective are these capabilities in enhancing resilience across shocks. The two important shocks, that took place after Lindbloom's study, namely the farm income decline in 2015 and the US-China trade war of 2018, present opportunity for further research to answer these open questions.

This study aims to build on Lindbloom (2018) and expand the farm resilience literature in three important ways. First, the time periods covered by this study include two most recent shocks in addition to shocks covered by Lindbloom (2018), specifically disruptions caused by commodity price fluctuation in 2015 and US - China trade war in 2018. Second, the causes and durations of specific shocks are more precisely defined. Third, an expanded range of farm characteristics is incorporated as variables in the empirical model to account for adaptive capabilities and for potential non-linear relationships between farm characteristics and resilience.

The specific objectives of this study include: (i) measuring the resilience of Kansas agricultural producers at the individual farm level during four shocks in the 1973-2021 period, and (ii) estimating an enhanced empirical model to gain more insights on the effect of farm level resources and capabilities on its ability to withstand (buffer) and restructure (adapt) during the exogeneous shocks.

To achieve the first objective, this study utilizes the Resilience Triangle approach method proposed by Bruneau et al. (2003) and used in Lindbloom (2018). The method enables computation of resilience index value based on three factors: (1) performance measure, (2) magnitude of impact, and (3) time to recovery. To calculate resilience index values for an individual farm i for a shock period j, the *Resilience Triangle* framework is applied to the data obtained from the Kansas Farm Management Association (KFMA), which contains detailed farm-level financial and production information for Kansas farms between 1973 and 2021. Next, a set of farm characteristics is defined and classified as buffering and adaptive capabilities based on economic theory and practical logical reasoning. Such characteristics include diversification, debt-to-asset ratio, depreciation ratio, and crop inventory as buffering capabilities; change in revenue diversification, change in acre diversification, and change in expense ratio as adaptive capabilities; and average government payment percentage of net farm income, age of farm operator, and farm size as demographic control variables. These variables served as input for the empirical model that was defined as part of the second objective and estimated using fractional logit regression (Papke & Wooldridge, 1996).

The reminder of the thesis is structured as follows: Chapter 2 presents the review of literature on resilience in general and in the context of agriculture; Chapter 3 presents a detailed description of the conceptual framework; Chapter 4 presents the data and summary statistics, followed by the description of analysis in Chapter 5; the results and discussion are presented in Chapter 6, followed by conclusions in Chapter 7.

Chapter 2 - Literature review

The resilience triangle method first introduced by Bruneau, et al. (2003) was the fundament for the quantitative analyses and system resilience research. Literature shows that after the introduction of resilience triangle method, it has been adopted and applied in various industries ranging from a business organization supply chain (Sheffi & James, 2005) to a Portuguese automotive supply chain (Barroso, Machado, Carvalho, & Cruz Machado, 2015) to a Chinese agricultural supply chains (Yang & Xu, 2015).

The agricultural system resilience generally can 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 (Lindbloom M. B., 2018). Early research in the existing body of literature suggests that adaptation during and after the shocks is one of the most important capabilities of agricultural systems resilience (Darnhofer, et al. 2009, Milestad, et al. 2012). Moreover, Darnhofer, et al. (2009) in their study about the role of adaptiveness in the sustainability of farming identified three strategies that strengthen the adaptive capacity of a farm: (i) learning through experimenting and monitoring its outcomes, (ii) ensuring a flexible farm organization to increase the options for new activities by the farm family, and (iii) diversifying to spread risks and create buffers (Darnhofer, et al. 2009). While the existing literature identifies the essential components of agricultural system resilience, it is lacking quantitative measurement of resilience at farm level.

Studies of resilience in agriculture examined the role of farm size and economies of scale. While on one hand, large size and economies of scale can be resilience enhancing factors through their impact on cost, on the other hand, large farms can be less flexible and slow to adapt to external change thus inhibiting their resilience to external shocks. At the same time, research in agricultural system resilience were in search of specific factors that may potentially have influence on the agricultural resilience. For example, early research has shown that diversified farms are more likely to withstand simultaneous disturbance in a system meanwhile maintaining productivity (Featherstone & Moss, 1990; Purdy, Langemeier, & Featherstone, 1997). In more recent researches Lin (2011) or Kremen and Miles (2012) suggest that diversification may potentially help farms to better withstand the potential shocks from the perspective of managerial practice.

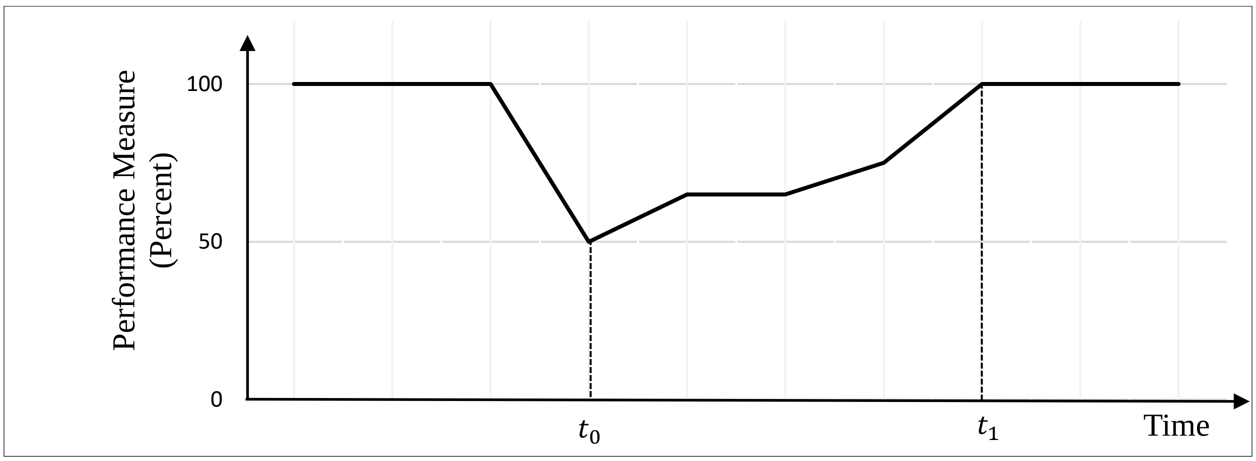
While the body of literature on agricultural resilience is growing, motivated by a number of recent unprecedented shocks, there are still a number of well-defined gaps. Specifically, there is a disproportionately large body of qualitative studies discussing theoretical and conceptual approaches to understanding resilience in agriculture. In contrast, the body of quantitative studies is limited to a handful of studies that attempt to directly measure resilience and estimate the effect of various factors (Lindbloom 2018; Lindbloom, et al. 2022). This study attempts to fill this gap by extending the body of quantitative research on farm resilience.

Chapter 3 – Conceptual Framework

3.1 The Resilience Triangle Approach

Figure 1 is the graphical representation of the resilience triangle approach first introduced in the engineering literature (Bruneau, et al., 2003). It combines two primary components of resilience: performance measure and time. In this specific example, performance ranges from 0% to 100%. During the post-shock period the performance is 100%. When at time point t_0 shock happens, the performance drops to 50%. The recovery process is expected to occur from time-period t_0 until t_1, when it is fully recovered. In other words, the performance measure returned to its initial value (100%) before the shock. (Bruneau, et al., 2003)

Figure 1: Resilience Triangle (Bruneau, et al, 2003)



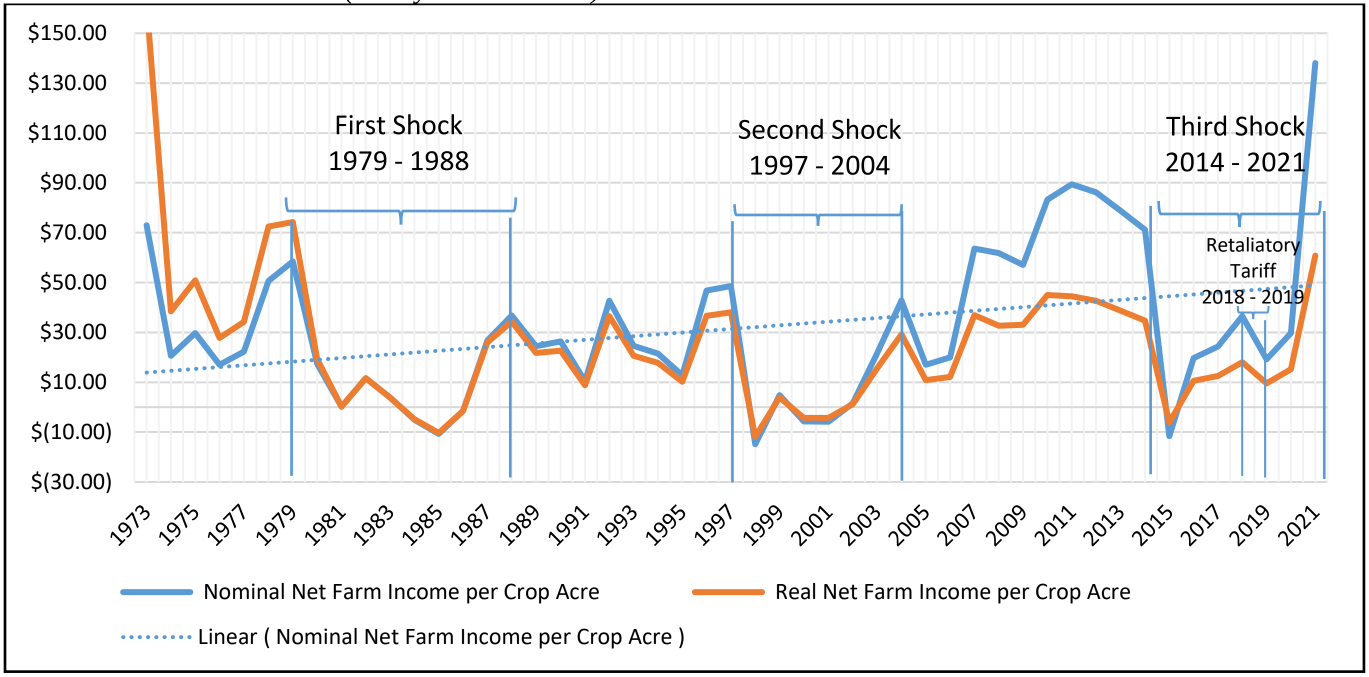
The above-mentioned resilience triangle method has two main components: performance measure and time, or time periods. For this analysis, the Real Net Farm Income per Crop Acre (RNFI) has been selected as a performance measure indicator to be the basis for computing the farm resilience triangle. In general, Net Income is the most traditional financial performance measure. It is an indicator of past farm resource management decisions and can reflect the impacts of a shock on the fundamental functioning of the system. Nevertheless, net farm income is the most sensitive to changes in levels of production or prices. If RNFI declines, it will be a result of either an increase in farm expenses, a decrease in the value of farm production, a drop in sales, or all the above (Lindbloom, 2018; Lindbloom, et al. 2022).

3.2 Shock Periods

The next step is to identify the shock periods that impacted Kansas agriculture. In the previous study, Lindbloom (2018) identified two shock periods based only on the KFMA data observations for a time span from 1973 to 2014. For this study, the data have been updated to cover a time span from 1973 to 2021, which includes two additional shock periods: the commodity price decline of 2015 and U.S.- China trade of 2018. In addition, this study has a different approach to identifying the shock start and end-time points. First, it looks at the historical facts and literature to define the presence rather than the shock's cause. Afterward, if KFMA data shows the decline in statewide farm average performance (Net Farm Income per Acre) during that specific time, then that point has been chosen as the beginning of the shock. The end of the shock is determined using the same approach.

To begin, real and nominal net farm incomes per acre for 8,548 farms have been graphed as a time series and represented in Figure 2. Alongside Figure 3 is a graphical representation of nominal and real net farm incomes. From both figures, it is observable that over time, both net farm income (NFI) and net farm income per crop acre in Kansas (NFI crop acre) have been fluctuating. However, three distinct periods stand out. Drop in net farm income in 1979, a drop in net farm income in 1998, and a drop in net farm income in 2015.

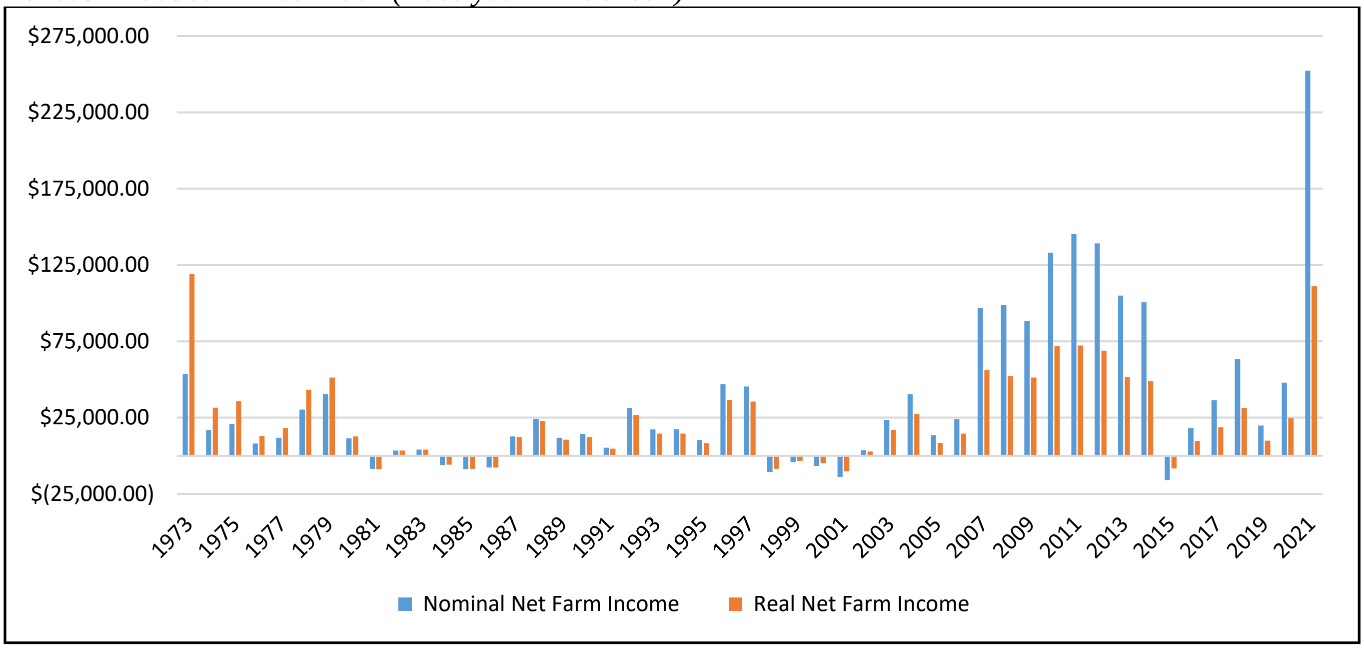
Figure 2: Average value of real and nominal net farm income per crop acre, 1973-2021, Kansas; U.S. Census Bureau Producer Price Index (Base year = 1982:84)



In 1979 The Federal Reserve changed its monetary policy, which significantly impacted all areas of the US economy. Particularly the agricultural sector was severely disrupted. The following year after the changes had been adopted would be announced as the beginning of the "Farm Financial Crisis of the 1980s," which lasted until 1987-88 (Barnett, 2000). KFMA data confirms the drop in net farm income in 1979 and recovery in 1988. Consequently, the time period of the first shock for the study has been chosen from 1979 to 1988.

The second distinct drop in net farm income happened in 1997 - 1998. This drop in net farm income was a result of the Federal Agriculture Improvement and Reform Act of 1995-96, also known as Freedom to Farm Act (H.R.2195 - 104th Congress, 1995-1996). According to the reform the government promoted the exports of farm products in Latin America and new trade deals with the World Trade Organization (WTO) by reducing farm subsidies. Unfortunately, the strategy that supposed to led to export growth followed by the trade balance crash (Scott, 2000). In 1998 compared to 1996 U.S corn and wheat prices dropped 56 and 46 percent respectively. According to the KFMA data in Kansas, net farm income declined by 124% compared to the previous year and declined to negative levels. Real net farm income was approximately negative $10 per crop acre. This was the second largest drop in net farm income since the farm financial crisis of the 1980s. Unfortunately, this time Kansas farmers needed a longer time to recover. Net farm income started to go up in 2002 but did not reach its initial point before shock until 2004. Therefore, the second shock period for the analysis has been chosen from 1998 to 2004.

Figure 3: Average value of real and nominal net farm income, 1973-2021, Kansas; U.S. Census Bureau Producer Price Index (Base year = 1982:84)

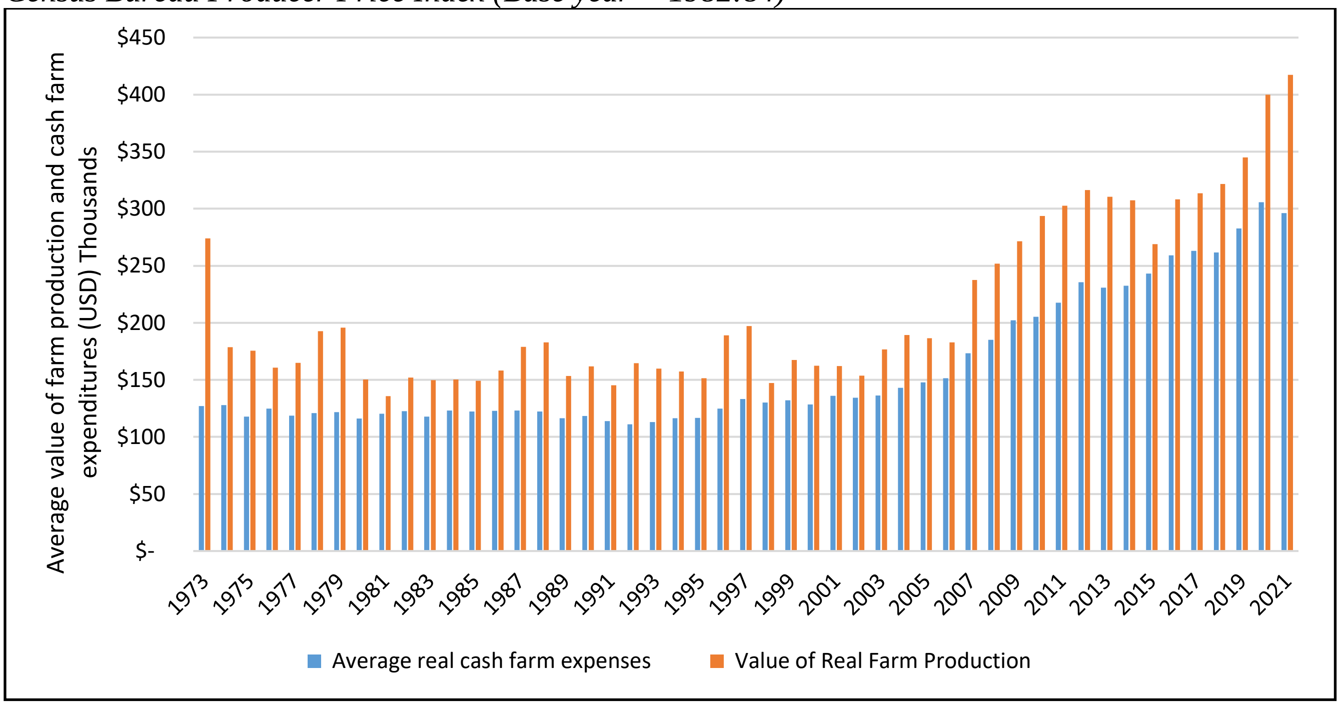


The beginning of the third shock period has been chosen as 2015. Indeed, it was the second largest drop in net farm income per crop acre in Kansas since 1998. This time the agricultural sector had been exposed to low commodity prices. In 2015, USDA projected a drop in net farm income, unfortunately they did not know that they predicted the beginning of another shock period in Kansas. Net farm income climbed back above its trend line in 2021, consequently the end of the third shock period has been identified as 2021.

Moreover, the third shock period from 2015 to 2021 includes an additional sub-shock period caused by a retaliatory tariff imposed by China against U.S. exports from 2018 to 2019 (Fajgelbaum & Khandelwal, 2022). It is important to mention that KFMA reports data at the end of the year, therefore the shock period for retaliatory tariff has been chosen from 2018 to 2019.

To determine whether each shock was caused by revenue declines, cost increases, or both, the real average value of farm production and real average cash farm expenses for 8,554 KFMA farms between 1973 and 2021 were examined in Figure 4.

Figure 4: Average value of farm production and cash farm expenditures (USD) Thousand; U.S. Census Bureau Producer Price Index (Base year = 1982:84)



It is important to mention that farm expenses include hired labor, machinery repairs, building repairs, paid interest, purchased feed, seed and other crop expenses, fertilizer and lime, machine hire, organization fees, vet-medicine drugs, crop storage and marketing, livestock marketing and breeding, gas-fuel-oil, real estate, personal property taxes, general farm insurance, utilities, cash farm rent, herbicide and insecticide, conservation, and auto expense. The data indicate that for all three shock periods, the drop in average RNFI was caused by both a decline in the value of farm production and an increase in farm expenses.

Chapter 4 - Data & Summary Statistics

The data for this research is obtained from the Kansas Farm Management Association (KFMA), which contains detailed farm-level financial and production information for farms in Kansas between 1973 and 2021. To qualify for the resilience analysis in this study, farms have to meet two criteria; (i) farms that produced crops during the four shock periods, and (ii) farms that were operational for the entire duration of each shock period. This resulted in a sample of 1,417 farms, including 269 farms for shock one, 643 farms for shock two, 357 farms for shock three, and 144 farms for shock four. It is likely that there was a sub-sample of non-resilient farms that did not survive after earlier shocks and as a result were excluded from the sample. This does not have significant implications for the findings, because the analysis is focusing on factors that can enhance resilience (i.e., what did the most resilient farms do right). In other words, the population of inference based on this sample includes farms that survived all shocks. Within that population there is a distribution based on resilience level (e.g., less resilient to more resilient). The study examines in which way the more resilient farms are different from less resilient and how those differences may have affected the resilience.

Table 1 presents summary statistics by six regions of Kansas during each shock period. It is important to mention that average values were computed during the shock time period, and real net farm incomes do not include government payments.

During the first shock period, the greatest number of observations were in the Southcentral region and the least in the Northwest region. The largest farms in terms of average acres operated were in the Northwest region, while the smallest farms were in the Northcentral and Southcentral regions. On average, the highest government payments were received by farmers in the Southwest region, while farms in the Southeast region received the least amount. The Northeast region had the highest average real net farm income and real net farm income per crop acre, while the lowest was in the Northwest region.

Table 1: Summary Statistics by Geographic Region

	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
First Shock Period (1979 – 1988)						
Number of Observations	18	36	34	71	47	68
Avg. Age	46	51	47	48	45	48
Avg. Acres Operated	2,754	2,244	1,201	1,205	1,380	1,330
Avg. Real Gov. Payment	$22,123	$25,305	$11,180	$16,418	$11,550	$9,351
Avg. Real NFI	$7,997	$5,533	$11,532	$7,466	$21,316	$14,921
Avg. Real NFI Crop/Acre	$3	$2	$16	$13	$35	$23
Second Shock Period (1998 - 2004)						
Number of Observations	38	34	111	139	108	208
Avg. Age	49	54	50	51	52	52
Avg. Acres Operated	2,846	2,380	1,605	1,790	1,575	1,813
Avg. Real Gov. Payment	$43,115	$34,746	$23,214	$29,770	$25,037	$24,001
Avg. Real NFI	($8,069)	($1,623)	($457)	$3,093	$8,428	$8,977
Avg. Real NFI Crop/Acre	($3)	$1	$2	$2	$7	$4
Third Shock Period (2015 - 2021)						
Number of Observations	27	7	116	38	81	87
Avg. Age	44	65	58	59	60	59
Avg. Acres Operated	4,480	2,768	2,071	2,428	1,534	2,486
Avg. Real Gov. Payment	$42,938	$37,652	$27,502	$31,972	$20,910	$30,049
Avg. Real NFI	$27,255	$36,365	$24,413	$28,444	$32,582	$51,490
Avg. Real NFI Crop/Acre	$4	$13	$17	$11	$22	$27
Fourth Shock Period (2018 - 2019)						
Number of Observations	35	6	87	26	77	84
Avg. Age	48	68	59	63	61	62
Avg. Acres Operated	4,834	2,599	2,030	2,069	1,468	2,645
Avg. Real Gov. Payment	$21,250	$28,053	$16,354	$20,313	$14,187	$15,929
Avg. Real NFI	$45,048	$16,980	$15,233	$19,532	$16,787	$69,781
Avg. Real NFI Crop/Acre	$12	$9	$12	$11	$6	$30

*Average values are computed during shock time-period
**NFI does not include Government payments

Moving to the second shock period, the Southeast region had the greatest number of observations, while the Southwest region had the least. Similar to the first shock period, the largest farms in terms of average acres operated were in the Northwest region, while the smallest farms were in the Northcentral and Southcentral regions. The highest governmental payments were received by farmers in the Northwest region, and the least amount received in the Northeast region. The highest average real net farm income was in the Northeast and Southeast regions, while the lowest was in the Northcentral region. The highest real NFI per crop acre was in the Southeast region, and the lowest was in the Northwest region.

During the third and fourth shock periods, the greatest number of observations were in the Northcentral region, while the least was in the Southwest region. The largest farms were in the Northwest region, while the smallest farms were in the Northeast region. Northwest regions during both shock periods received the highest government payments, while the Northeast received the least. The highest real NFI income and real NFI per crop acre were in the Southeast region.

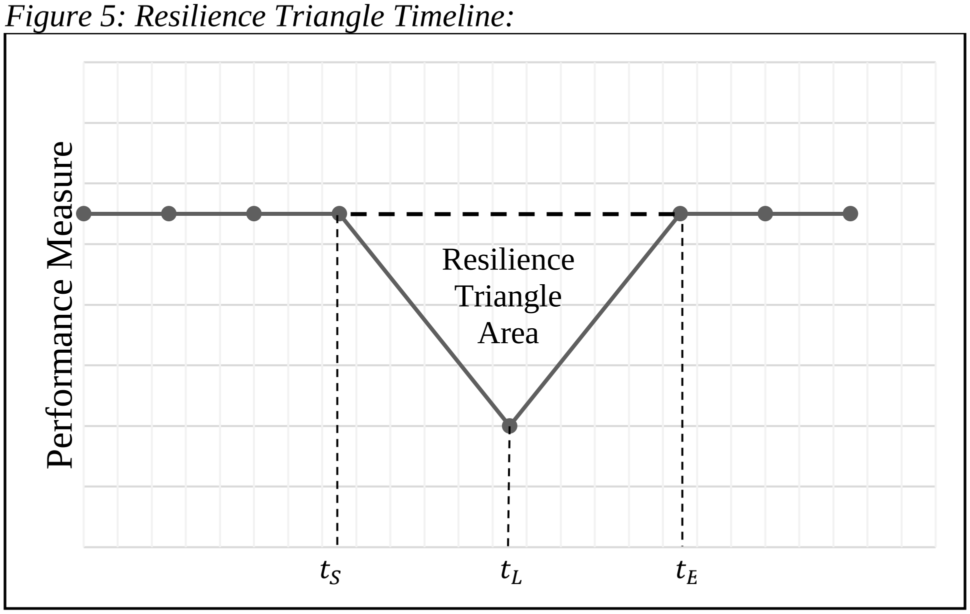
In conclusion, summary statistics show that the effect of the shocks varied across regions. During each shock period, the impact was unique on the regions, which may be attributed to the unique character of the shocks, the regional differences in farm operations, and other factors such as infrastructure and agroecological conditions.

Chapter 5 - Analysis

5.1 Resilience Index Values

Resilience index values are computed using a similar method proposed by Lindbloom (2018). However, in Lindbloom's (2018) analysis, the chosen performance measure (Real NFI per Crop acre) includes government payments. In contrast, this study excludes government payments from real net farm income per crop acre. The logic behind that is that government payments may directly reflect the on-farm decision making and capabilities. Therefore, including any source of income in the chosen performance measure that does not reflect on-farm capabilities and decision making will likely lead to biased results by inflating the resilience index values. Further, in this study the government payments are incorporated in the right-hand side of the analytical model as a contributing factor in calculating the revenue diversification index.

Figure 5: Resilience Triangle Timeline:



In order to compute resilience index values, a clear set of distinct time periods must be specified. Figure 5 represents the resilience triangle framework where t_s is the starting point of the shock, t_L is the lowest point of the shock, and t_E is the ending point of the shock.

Note that the time points of statewide shock periods are based on average farm performance. However, start and end dates are unique at the individual farm level, which means that each farm shock can have different start and end dates. Therefore, in order to determine t_s for a farm i, the real net farm income per crop acre needs to meet two conditions. First, it needs to be greater than or equal to the RNFI in the preceding period. Second, RNFI per crop acre needs to be strictly greater than real net farm income per crop acre in the period immediately after:

Condition 1:

$$NFI_{t_S} \geq NFI_{t_S-1} \;\;\&\;\; NFI_{t_S} > NFI_{t_S+1}$$

Condition 1 determines the initial starting point of the shock for each farm. For example, if the NFI experienced an increase before a given year and after that year it dropped that given year was chosen as the beginning of the shock period for the individual farm. It was possible that during the shock period there would be multiple points that satisfy condition 1 as NFI fluctuates year by year. Therefore, for the start point of the shock was chosen the first point that satisfy the condition 1 during the pre-determined period of shock beginning based on the state average data.

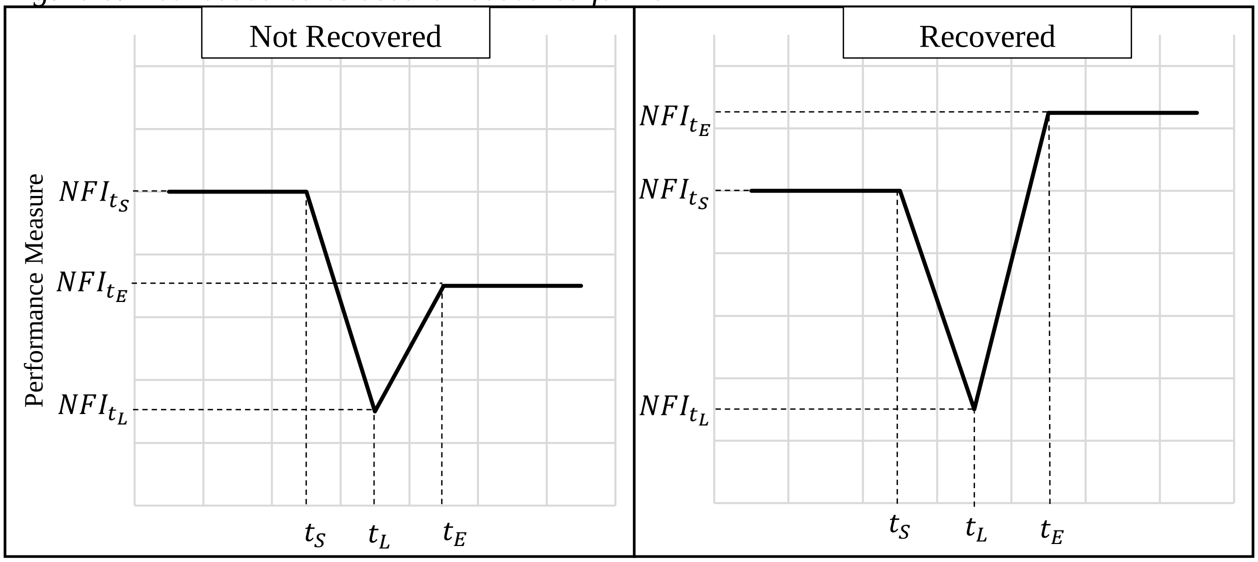
Next, to determine t_E: the endpoint for each farm for the specific shock has been applied condition 2:

Condition 2:

$$NFI_{t_E} \geq NFI_{t_S}$$

This condition states that in order to determine real net farm income at the end of the shock period, it should be greater than or equal to the real net farm income per crop acre during the start of the shock period. From this condition there are two possible scenarios. The first scenario is if the condition does not meet the requirement, which will mean that the farm did not recover from the shock (as shown in the left graph in figure 6). In that case, the resilience index has been computed using the statewide end date of the shock.

Figure 6: Not recovered vs ascend recovered farms



In the second scenario, it is possible that the real net farm income per crop acre at the endpoint of the shock (NFI_{t_E}) will be greater than the real net farm income per crop acre at the start point of the shock (NFI_{t_S}) (see right graph in figure 6). In this case, the real net farm income per crop acre at the endpoint of shock (NFI_{t_E}) has been set to be equal to the real net farm income per crop acre at the start point of the shock $\left(NFI_{t_S}\right)$. This condition has been applied in order to normalize the size of the resilience triangle area. If not doing so, it is possible for some farms to recover above the initial start point, which will create a bigger triangle and a false perception that the farm was not resilient.

The next step is to determine t_L time point when the individual farm's performance measure (net farm income per crop acre) has the lowest value during the shock period. For that, condition 3 has been applied.

Condition 3:

$$NFI_{t_S} \geq \min NFI_{t_L} \leq NFI_{t_E}$$

Finally, the resilience index values have been computed by using the following equation:

Equation 1:

$$R_i = \left(\frac{t_L\left(NFI_{t_s} - NFI_{t_E}\right) + t_S\left(NFI_{t_E} - NFI_{t_L}\right) + t_E\left(NFI_{t_L} - NFI_{t_S}\right)}{2}\right)^{-1}$$

This is the inverse of the area of the triangle resulting from connecting three points, the pre-shock real net farm income (NFI_{t_S} at time t_S), the lowest real net farm income during the shock (NFI_{t_L} at time t_L), and the real net farm income at the end of the shock period (NFI_{t_E} at time t_E). The resilience index is calculated at the individual farm level. While the shock period is based on average farm performance, the reduction in real NFI as a result of the shock can happen at different times for each farm. Consequently, the resilience index for each farm is calculated using the period with an initial drop in real NFI for that particular farm during each shock period.

5.2 Empirical model

The empirical model specification follows the approach in Lindbloom (2018). However, the methods for calculating some of the variables are different, as well as this study includes a few additional variables. The variables are described in detail below.

First, in order to distinguish explanatory variables, based on the literature they have been categorized into three different capabilities of resilience: buffering, adaptive and transformative. Daugstad (2019) states that the buffering capability is an ability of adopting to the change without affecting the operation of the agricultural system. Adaptive capability is capacity to grow within the present framework which may include adopting new technology or altering the properties of a product. Transformative capability is a capacity of undertaking drastic changes and being able to implement transitions such as changing from milk production to agrotourism.

5.2.1 Buffering Capability Variables

The first variable that has been chosen to represent and measure the farm's buffering capability is a diversification index. Previous studies posited that diversification of farm production is a buffering capability that can enhance the ability to respond to external shocks, in other words it can strengthen the resilience (Featherstone & Moss, 1990; Lin, 2011; Kremen & Miles, 2012).

The diversification index was calculated for each farm as a reflection of buffering capability. The calculation of diversification index was based on the Herfindahl-Herschman (HH) index (Rhoades, 1993). It has been developed to measure market concentration, thus by adopting it in this study makes it possible to measure concentration of different types of crops on operating crop acres at an individual farm level. The diversification index used in the analysis reflects the total of crop acre diversification levels during the shock' periods and was computed as shown in Equation 2. Then the value of the crop diversification index for the three years prior to the shock was computed as shown in Equation 3.

Equation 2:

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

Equation 3:

$$AvgD_i = \left[\sum_{n=t_{s-1}}^{t_{s-3}} D_i^n\right] \times \frac{1}{3}$$

where D_i is the diversification level of farm i and $AvgD_i$ is the average diversification level of farm i during three years prior to the shock. TAP_k refers to the total acres planted to crop k, and TAP is the total acres planted. The k crops include dry and irrigated acres of wheat, corn, grain sorghum, soybeans, sugar beets, alfalfa, silage, other grain, other hay, and other cash crops. Now if diversification index $D_i = 1$, it will mean that farm is not diversified, and it dedicated 100% of acres to a single crop, on the other hand, for a highly diversified farm the value of D_i will be close to zero.

The next variable chosen to measure a farm's buffering capability is the average debt-to-asset ratio three years prior to the shock. Literature suggests that by lowering the debt-to-asset ratio a farmer may potentially increase the profitability of the business (Purdy, Langemeier, & Featherstone, 1997; Mishra, El-Osta, & Steele, 1999). Debt-to-asset ratio has been computed as shown in Equation 4

Equation 4:

$$AvgDAR_i = \left[\sum_{n=t_{s-1}}^{t_{s-3}} \left(\frac{ST\ Debt + LT\ Debt}{Total\ assets}\right)\right] \times \frac{1}{3}$$

Where $ST\ and\ LT\ Debts$ are short and long-term debts.

The third variable that has been chosen to measure a farm's buffering capability is the average value of crop inventory three years prior to the shock. Literature suggests that excess capacity may act as a buffering capability during economic or environmental shocks (Darnhofer, at al. 2014; Rose, 2009). Indeed, the crop or grain inventories can serve as a liquid asset and quickly be transformed into cash during an economic shock, hence it can be served as a buffering capability. Therefore, excess grain inventories may act as a buffering capability as it is a primary asset that may be sold during shock times. The variable has been calculated as shown in Equation 5:

Equation 5:

$$AvgCropInv_i = \left[\sum_{n=t_{s-1}}^{t_{s-3}} (BGI + BHFI + BCC)\right] \times \frac{1}{3}$$

where $BGI, BHFI$, and BCC are the beginning of grain, hay and forage, and crop inventories.

The last variable that is chosen to measure a farm's buffering capability is the average depreciation expense ratio in the three prior years to the shock. This variable is added to the original specification in Lindbloom's (2018) study. The logic behind including the depreciation expense ratio in this study as a buffering capability is that it can be used as an indicator of farms foresight and ability to plan for bad years during good years. For example, in good years many producers would spend money on equipment to reduce tax burden, which can arguably affect their financial position during a future unanticipated shock. The variable has been calculated as shown in equation 6.

Equation 6:

$$AvgDepRatio_i = \left[\sum_{n=t_{S-1}}^{t_{s-3}} \frac{VPD + MED + BD}{RNFI} \right] \times \frac{1}{3}$$

where VPD is motor vehicle and listed property depreciation, MED is machinery and equipment depreciation, BD is building depreciation and $RNFI$ is real net farm income.

5.2.2 Adaptive Capability Variables

Adaptive capability is defined as a capacity to change in order to adapt to the shifts in external and internal environment which may include adopting new technology or implementing operational changes (Daugstad, 2019). According to Darnhofer at al (2014) it is not necessary to undergo a fundamental change. Thus, the variables reflecting adaptive capabilities are computed based on the change between pre-shock level and the recovery level.

The first variable that is chosen to measure adaptive capability is the change in the level of revenue diversification between pre-shock level and the recovery level. It is calculated by taking the difference between the average revenue diversification pre-shock and that of the recovery period (i.e., period between the lowest point and the end point). It has been calculated similar to Equations 2 and 3, but instead of crops, the available information on revenue is used, which includes livestock production, off-farm work, government payments, and other product sales. The logic behind including the variable as an adaptive capability is that during the shock farmers making adjustments to prevent the loses in net farm income (Lindbloom M. B., 2018)

The next variable that is chosen to measure adaptive capabilities of farm is change in average acre diversification from shock to pre-shock levels. To compute the change in acre diversification has been taken the difference between $AvgD_i^p$ (average diversification during three years prior to the shock, i.e., pre-shock diversification) and $AvgD_i^r$ (average diversification during the years between the lowest performance year to the end year, i.e., recovery years).

The last variable that is chosen to measure adoptive capabilities is the change in average expense ratio. Mishra, El-Osta, & Steele (1999) mentions that those farms that can minimize production costs per crop acre are capable of optimizing output per unit. The variable that has been computed as shown in Equation 7.

Equation 7:

$$AvgOER_i^p = \left[\sum_{n=t_S-1}^{t_{S-3}} \frac{Operating\ Expenses}{Value\ of\ Farm\ Production}\right] \times \frac{1}{3}$$

$$AvgOER_i^r = \left[\sum_{n=t_S}^{t_l} \frac{Operating\ Expenses}{Value\ of\ Farm\ Production}\right] \times \left(\frac{1}{t_E - t_S}\right)$$

$$\Delta OER_i = OER_i' - OER_i$$

where $AvgOER_i^p$ is the average operating expense ratio for the three years prior to the shock and $AvgOER_i^r$ is the average operating expense ratio for the recovery period (i.e., from time period t_L to time period t_E).

5.2.3 Other Variables

Other variables included in the model are the average government payments proportion of RNFI and its square term. The square term of the average acre diversification index, the square term of the debt-to-asset ratio and the square term of the average depreciation ratio. The square terms are included in the model in order to capture potential nonlinear effects on resilience. The control variables include: the age of the primary operator ($\mathrm{Age_i}$) at the start of the shock and the square of the age ($\mathrm{Age_i^2}$), average size of the farm in acres ($\mathrm{Acre_i}$) and its square term ($\mathrm{Acre_i^2}$), which is calculated for the duration of the shock, and binary control variables reflecting shock periods ($\mathrm{Time_i}$) to capture the effect of differences between shock periods. All square terms of variables, except square age and square acre, are additions to the Lindbloom's (2018) model. All the variables that are used to represent resilience capabilities are summarized in table 2.

Table 2: Summary of variables

Capability Variables		Variable description
Buffering	$AvgD_i$	Average Diversification of crop acres prior to the shock
	$AvgDAR_i$	Average dept-to-assets ratio prior to the shock
	$AvgCropInv_i$	Average value of crop inventory prior to the shock.
	$AvgDepRatio_i$	Average depreciation expense ratio prior to the shock
Adaptive	$\Delta AvgRD_i$	Change in average revenue diversification
	$\Delta AvgD_i$	Change in average crop acre diversification
	$\Delta AvgOER_i$	Change in average operating expense ratio
Other	$AvgD_i^2$	Square term of average diversification of crop acres
	$AvgDAR_i^2$	Square term of average dept-to-assets ratio
	$AvgDepRatio_i^2$	Square term of average depreciation ratio
	$AvgGP_i$	Average government payments percent of RNFI
	$AvgGP_i^2$	Square term of average gov. payments percent of RNFI
	Age_i	Age of the primary operator at the start of the shock
	Age_i^2	Square term of the age
	$Acre_i$	Average size of the farm during the shock
	Acre_i^2	Square term of average size
	$Time_i$	Second, third, and fourth shock periods

The model is estimated using logistic fractional response model estimation method and the results are computed using Stata software

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Chapter 6 - Results

6.1 Discussion of Resilience Index Values

The first objective of the study is to measure resilience index values for all four shock periods from 1980 to 2021 at the individual farm level. The results of the resilience index values are presented in Table 3.

The Southwest region was the most resilient region during the first shock period. Moreover, 59% of all observations from the Southeast region had strong recovery (meaning post-shock real NFI per crop acre was greater than pre-shock real NFI per crop acre). The least resilient region was the Southeast region. During the second shock period, the most resilient region was Northwest with the most amount of the fully recovered farms (32%). Moving from Frist to Second shock period statewide average resilience index dropped almost by 27%. This extensive drop in statewide average resilience index values indicates that the second shock period was more severe than the first shock which was due to the farm financial crisis.

The study conducted by Lindbloom (2018) showed that a statewide average resilience index values increased from shock one to shock two. This difference in findings may be due to the fact that Lindbloom included government payments in his analyses while computing resilience index values.

Moving from shock period two to shock period three, statewide average resilience index values increased to around 34%. During the third shock period, the most resilient region was the Southwest region, with 57% total recovered farms. The least resilient were Northcentral, Southcentral, and Northeast regions with a similar resilience index value. However, during the third shock period, the least recovered farms were from the Northcentral region.

During the fourth shock period statewide average resilience index values were relatively high, compared to the previous shock periods. The most resilient region was the Northwest region while the least resilient was the Southeast region.

Table 3: Resilience index values (Index values are multiplied by 10)

	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
First Shock Period						
Number of Farms	16	34	35	71	46	67
Fully Recovered Farms	50%	59%	71%	48%	52%	58%
Resilience Index	0.081	0.110	0.091	0.081	0.066	0.046
Second Shock Period						
Number of Farms	38	34	111	138	109	213
Fully Recovered Farms	32%	26%	24%	26%	28%	24%
Resilience Index	0.105	0.091	0.061	0.065	0.037	0.037
Third Shock Period						
Number of Farms	28	7	116	38	81	87
Fully Recovered Farms	36%	57%	18%	37%	27%	20%
Resilience Index	0.117	0.502	0.055	0.055	0.057	0.068
Fourth Shock Period						
Number of Farms	11	-	42	-	48	36
Fully Recovered Farms	73%	-	81%	-	88%	56%
Resilience Index	0.334	-	0.241	-	0.291	0.198

* “-“denotes regions excluded from the analysis due to less than five observations

It is important to mention that the fourth shock period took place while Kansas farmers had not yet recovered from the third shock period. Moreover, the results are showing that during the fourth shock period, the resilience index values were relatively higher compared to the previous shock periods, which indicates that the fourth shock that was due to tariff increase was not severe compared to other shock periods. It lasted relatively a shorter time (two years) than the other shocks. The fourth shock that was due to a tariff increase was not severe compared to the other shock periods. Overall, it is logical that during different shock periods the same region will have different endurance and resilience index values, as every shock has a unique character. For instance, first shock period was due to farm financial crisis which had a longer and more severe outcome than the shock period four which was due to export tariffs imposed by China against U.S. and lasted just two years. Therefore, it was logical to see higher resilience index values during shock period four compared to shock period one. Some of the regional variation in resilience can be attributed to variations in crops planted and specific agro-ecological differences (e.g., irrigated vs non-irrigated operations). However, to find out the exact causes for the differences in resilience across the regions further research should be conducted.

6.2 Discussion Resilience Capability Variables

Table 4 represents summary statistics by region for all shock periods for the resilience capability variables. The highest average debt-to-asset ratio prior to the first shock period was in the Northwest region (38%) while Northcentral, Northeast, and Southeast regions had almost the same debt-to-asset ratio ranging from 24% to 35%. The most diversified region was Northeast and the least diversified was Northwest region. The highest average value of crop inventories was held by farmers in the Southwest region while the lowest was in the Northcentral region. Northcentral region had the highest depreciation ratio while the lowest depreciation ratio had farmers in Northwest and Southwest regions. Change in acre diversification was negative for all the regions, indicating that during the shock, farms become more diversified. All regions experienced a positive change in the average operating expense ratio which means that during the shock, the average operating expense ratio increased in all the regions.

Prior to the second shock period, the highest debt-to-asset ratio was in the Northcentral region (37%), while the lowest was in Northeast region similar to the first shock (24%). The most diversified region was the Northeast region and the least diversified was the Southwest region. Farmers in the Northwest region were holding the highest value of average crop inventory value. The highest depreciation ratio was in Southcentral and Southeast regions while the lowest was in Northwest similar to the first shock period. Unlike the first shock period almost all the regions except Northeast experienced negative change in both revenue and acre diversification indicating that farmers during the shock become more diversified.

Table 4: Summary statistics of the farms' resilience capabilities by the region

Capabilities Variables	Northwest	Southwest	Northcentral	Southcentral	Northeast	Southeast
First Shock Period						
3-yr. Debt to Asset Ratio	38%	30%	27%	33%	24%	26%
3-yr. Acre Diversification	0.55	0.52	0.40	0.51	0.32	0.40
3-yr. Crop Inventory $	$73,886	$103,229	$41,136	$47,638	$57,905	$59,796
3-yr. Depreciation Ratio	-15%	4%	272%	51%	71%	44%
Δ Rev. Diversification	0.12	0.19	0.20	0.08	0.09	0.11
Δ Acre Diversification	-0.13	-0.10	-0.02	-0.02	0.00	0.00
Δ Oprt. Expense ratio	0.14	0.13	0.19	0.11	0.16	0.21
Second Shock Period						
3-yr. Debt to Asset Ratio	33%	28%	37%	30%	24%	29%
3-yr. Acre Diversification	0.46	0.54	0.38	0.49	0.34	0.40
3-yr. Crop Inventory $	$92,971	$80,981	$41,199	$55,014	$73,765	$76,667
3-yr. Depreciation Ratio	2%	39%	-29%	109%	32%	101%
Δ Rev. Diversification	-0.07	-0.20	-0.01	-0.11	0.04	-0.02
Δ Acre Diversification	-0.07	-0.04	-0.03	-0.06	0.02	-0.02
Δ Oprt. Expense ratio	0.21	0.11	0.20	0.14	0.28	0.20
Third Shock Period						
3-yr. Debt to Asset Ratio	14%	9%	19%	12%	17%	21%
3-yr. Acre Diversification	0.38	0.51	0.31	0.42	0.39	0.38
3-yr. Crop Inventory $	$135,235	$142,975	$112,974	$127,149	$134,408	$162,453
3-yr. Depreciation Ratio	-28%	46%	86%	45%	36%	63%
Δ Rev. Diversification	-0.01	-0.08	-0.11	-0.11	-0.09	-0.05
Δ Acre Diversification	0.03	-0.02	0.00	-0.02	0.04	0.08
Δ Oprt. Expense ratio	0.05	-0.28	0.05	0.10	0.13	0.06
Fourth Shock Period						
3-yr. Debt to Asset Ratio	19%	10%	19%	9%	15%	15%
3-yr. Acre Diversification	0.36	0.77	0.30	0.37	0.41	0.39
3-yr. Crop Inventory $	$144,331	$99,163	$105,259	$57,205	$138,161	$298,672
3-yr. Depreciation Ratio	85%	811%	-35%	-717%	13%	-2158%
Δ Rev. Diversification	0.07	-0.13	-0.05	-0.12	0.06	-0.19
Δ Acre Diversification	0.01	-0.13	0.02	0.00	0.02	0.06
Δ Oprt. Expense ratio	-0.18	-0.19	-0.06	-0.07	-0.08	-0.10

Prior to the third shock period all the regions had a similar debt-to-asset ratio except Southwest where it was the lowest (9%). The most diversified was the Northcentral region, while the least diversified was the Southwest region. Farmers in the Southeast region were holding the highest value of average crop inventory value. The highest depreciation ratio prior to the shock was in the Northcentral region. Likewise, to the second shock all the regions during the third shock period experienced negative change in revenue diversification. The Southeast and the Southcentral regions had a negative change in acre diversification, indicating that in the regions farms become more diversified while in the rest of the state farms become less diversified. Only the southwest region experienced a negative change in operating expense ratio.

During the fourth shock period Northwest and Northcentral regions had the highest debt-to-asset ratio prior to the shock, while the Southcentral had the lowest. The most diversified was the Northcentral region and the least diversified was the Southwest region. The highest average value of crop inventories was held in the Southeast region while the lowest was in Northcentral region. During the fourth shock period only Northcentral and Northeast regions did not experience negative change in revenue diversification, however all the regions had negative change in expense ratio indicating that the expenses to operate the farm increased during the shock.

Table 5 presents summary statistics of the farms' resilience capabilities by dividing farms into three categories. First are the farms that did not recover from any shock, the second category are the farms that fully recovered from one shock, and last one is these farms that fully recovered from two shocks. The average age of the farm's operator that has been able to withstand two shocks is 55. Average operating acres again is relatively higher for these farms that have been able to recover from two shocks. Moreover, statewide average resilience index values are relatively bigger for those farms that have been able to recover from two shocks (1.911). Hence, this supports the fact that more experienced farmers have been able to withstand two shocks in row, moreover, larger farms have more potential to withstand the shocks.

Table 5: Summery statistics of the farms' resilience capabilities

	Did not recover from any shock	Fully recovered in 1 shock	Fully recovered in 2 shocks
Number of Farms	720	564	134
Average Age	53	53	55
Average Operating Acres	1873	1959	1912
Average Resilience Index (×10)	0.0620	0.1045	0.1911
3-yr. Acre Diversification	40%	40%	41%
3-yr. Debt to Asset Ratio	26%	26%	19%
3-yr. Crop Inventory $	$80,028	$95,340	$130,479
3-yr. Depreciation Ratio	76%	-106%	9%
Avg. 3-yr GP % of NFI	198%	109%	103%
Avg. GP % of NFI During Shock	338%	467%	172%

**GP – Government Payment*
**NFI – Net Farm Income*
****GP, NFI and Crop Inventory are presented in real values; U.S. Census Bureau PPI (Base year 1982:84)*

Average acre diversification for the recovered and non-recovered farms are almost the same. The average 3-year debt-to-asset ratio for the farms that have been able to recover from two shocks is significantly less (19%) this indicates that the farms that have less debts are more resilient to the shocks. Moving forward, the analysis shows that the farms that have been able to recover had a relatively higher value of crop inventories. For the recovered farms, the depreciation ratio was significantly lower than for non-recovered farms. Moreover, these farms that had been able to recover from two shocks had the minimum depreciation ratio (12%).

Overall, this shows that maintaining diversification is not enough to withstand the shocks. Moreover, in order to be resilient and ready to endure the waves of shocks, farmers need to have set of skills like experience, enough acreage, maintain diversification level, keep debt-to-asset ratio at the minimums, maintain a stockpile of crop inventories, and keep depreciation ratio at the minimum levels. More specifically, analysis shows that using depreciation as an excuse to reduce tax payments during good days has even worse reflection on the farm performance during bad days.

6.3 Discussion of Econometric Model Estimation Results

Table 6 presents the results of fractional logit estimates. Before conducting the analysis three sample specifications are made: a total sample of 1,408 observations, (ii) a sub-sample of 511 recovered crop farms only, and (iii) a sub-sample of 897 non-recovered crop farms only.

The parameter estimate for debt-to-asset ratio is positive for all the samples except for non-recovered farms, while the parameter estimate for the square term is negative again for all the samples except for non-recovered farms. This result shows that while the debt-to-asset ratio increases the resilience increases to some level above which the increase of debt-to-asset ratio will lead to the decrease of resilience. This result is logical, as the higher level of debt-to-asset ratio is associated with a higher risk, meaning that during the shock period farm may not be able to make a payment and eventually will go bankrupt.

The parameter estimate for crop acre diversification is positive for all the samples and statistically significant only for recovered farms, while the square term of the parameter estimate is negative for all the samples except for non-recovered. It is important to mention that the diversification index is calculated in a way that higher values mean less diversified and vice versa. Therefore, the results for total sample indicate that the increase in acre diversification will be associated with a decrease in resilience until the farm reaches some point of diversification, where the increase in diversification will lead to increase in resilience.

The results also indicate a statistically significant negative relationship between the value of crop inventory prior to the shock and the farm's resilience to the shock. Unfortunately, there is not a conclusive finding to show that crop inventories may serve as a buffering capability. Lindbloom's (2018) analysis shows the same results in terms of negative effect between value of crop inventories and farm resilience. This is likely due to the potential negative effect of the shock on prices, which might not be the case for all shocks.

The parameter estimate for change in revenue diversification is negative for all the samples and statistically significant for all the samples. These results indicate that an increase in revenue diversification is leading to an increase in resilience. Here it is essential to remember that revenue diversification includes off-farm income and government payments.

For all the samples, the parameter estimate for change in acre diversification is positive. Even though the parameter estimate is statistically not significant, this result is not surprising as it is reasonable to expect farms to abandon and/or reduce activities that became less profitable due to the shock. Thus, reducing the diversification of farm revenue may help farms to recover, as shown in the results.

The parameter estimate for the variable representing a change in the operating expense ratio is negative for all the samples and statistically significant for the total samples. This result indicates that, on average, if a farm is able to decrease its operating costs during the shock period then their resilience to the shock will increase.

The parameter estimates for the depreciation ratio and its square term are negative for all the samples and statistically significant for the total sample and recovered farms. This result indicates that an increase in the depreciation ratio will decrease resilience which confirms the logic that for a farm resilience it is important to maintain a low level of depreciation ratio.

The parameter estimates for average government payments percentage out of net farm income and its square term are negative for all the samples. These results indicate that, in general, an increase in the proportion of government payments of net farm income leads to a decrease in resilience. This result confirms the logic that the farm income should not rely on the government payments as it is meant to be a help to reduce the magnitude of the shock on the farm, rather than a form of income. Moreover, it once again confirms the fact that revenue diversification increases resilience.

Table 6: Results of fractional logit estimates

	Total sample		Recovered Farms		Not Recovered Farms	
R Index	Coef.	Marginal Effect	Coef.	Marginal Effect	Coef.	Marginal Effect
3-yr. Debt-to-Asset Ratio	0.2258	0.0018	0.4437	0.0054	-0.2764	-0.0016
	(0.3811)	(0.0032)	(0.7531)	(0.0093)	(0.4112)	(0.0024)
Sq. 3-yr. Debt-to-Asset Ratio	-0.0627	-0.0005	-0.1048	-0.0013	0.0456	0.0003
	(0.1122)	(0.0009)	(0.4167)	(0.0051)	(0.0895)	(0.0005)
3-yr. Acre Diversification	2.0702	0.0168	3.1675 *	0.0382 *	0.3076	0.0018
	(1.5963)	(0.0135)	(1.6698)	(0.0213)	(1.2143)	(0.0070)
Sq. 3-yr. Acre Diversification	-0.7284	-0.0059	-1.3491	-0.0163	0.4049	0.0024
	(1.2934)	0.0107	(1.3791)	(0.0170)	(1.1328)	(0.0067)
3-yr. Crop Inventory (10,000$)	-0.0224 ***	-0.0002 ***	-0.0229 ***	-0.0003 ***	-0.0232 ***	-0.0001 ***
	(0.0042)	(0.0000)	(0.0053)	(0.0001)	(0.0069)	(0.0000)
Chg. Rev. Diversification	-0.1854 ***	-0.0015 ***	-0.2279 **	-0.0028 **	-0.2078 ***	-0.0012 ***
	(0.0499)	(0.0004)	(0.0906)	(0.0012)	(0.0578)	(0.0003)
Chg. Acre Diversification	0.3026	0.0025	0.1171	0.0014	0.1724	0.0010
	(0.4931)	(0.0040)	(0.9413)	(0.0113)	(0.6367)	(0.0037)
Chg. Expense ratio	-0.6901	-0.0056 *	-0.5327	-0.0064	-0.6962	-0.0041
	(0.4760)	(0.0039)	(0.5488)	(0.0064)	(0.6753)	(0.0041)
Age	-0.0196	-0.0002	-0.0852 ***	-0.0010 **	0.0261	0.0002
	(0.0175)	(0.0001)	(0.0296)	(0.0004)	(0.0186)	(0.0001)
Sq. Age	0.0003	0.0000	0.0009 ***	0.0000 ***	-0.0002	-0.0000
	(0.0002)	(0.0000)	(0.0003)	(0.0000)	(0.0002)	(0.0000)
Average Acre	0.0002 ***	0.0000 ***	0.0004 ***	0.0000 ***	0.0002 *	0.0000 *
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Sq Acre	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000 **	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Depreciation Ratio	-0.0602 *	-0.0005 *	-0.1021 **	-0.0012 **	-0.0084	-0.0000
	(0.0312)	(0.0003)	(0.0433)	(0.0006)	(0.0069)	(0.0000)
Sq. Depreciation Ratio	-0.0001 *	-0.0000 *	-0.0001 **	-0.0000 **	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Avg. GP % of NFI	-0.0006	-0.0000	-0.0009	-0.0000	-0.0003	-0.0000
	(0.0005)	(0.0000)	(0.0019)	(0.0000)	(0.0003)	(0.0000)
Sq. Avg. GP % of NFI	-0.0008	-0.0000	-0.0004	-0.0000	-0.0008	-0.0000
	(0.0009)	(0.0000)	(0.0004)	(0.0000)	(0.0010)	(0.0000)
Shock 2	-0.4022 ***	-0.0033 ***	-0.3634 *	-0.0044 *	0.0660	0.0004
	(0.1236)	(0.0011)	(0.1938)	(0.0024)	(0.1293)	(0.0008)
Shock 3	-0.0769	-0.0006	-0.0607	-0.0007	0.4002 **	0.0023 **
	(0.1591)	(0.0013)	(0.2898)	(0.0035)	(0.1578)	(0.0010)
Shock 4	1.0939 ***	0.0089 ***	0.9173 **	0.0111 *	1.6159 ***	0.0094 ***
	(0.2762)	(0.0024)	(0.4443)	(0.0058)	(0.3774)	(0.0020)
Constant	-5.4479 ***		-4.1724 ***		-6.3879 ***	

In general, the results of the sub-samples and the total sample are consistent. However, the difference that stands out is that the variable of Age for recovered farms has a non-linear effect. This is not a controversial result. Moreover, summary statistics of the farms' resilience capabilities presented in Table 4 show that, on average, older farmers are more likely to withstand two or more shocks. This proves the logic that older farmers have more experience and are more likely to witness some sort of shock during the time that they have been in operation. Therefore, the non-linear effect of the parameter estimates for variable Age shows that, even though the increase in the average age of the operator will decrease the farm's resilience, after some point, it will have the opposite effect. However here it can be argued that if a farm experienced two or more shock periods the primary operator is going to be old. This question should be investigated in farther research.

While the parameter estimate for average acres is positive and statistically significant for all the samples, the square term of average acre is negative for all samples. This non-linear effect between average acre and square term of average acre indicates that an increase in farm acreage will lead to an increase in resilience until the point where the positive effect will turn into negative effect.

Chapter 7 - Conclusion

The purpose of this study is to build on the findings of Lindbloom (2018) and expand the literature on farm resilience in three main ways. First, the time periods covered by this study include two most recent shocks in addition to shocks covered by Lindbloom (2018), specifically disruptions caused by commodity price fluctuation in 2015 and US - China trade war in 2018. Second, the causes and durations of specific shocks are more precisely defined. Third, an expanded range of farm characteristics is incorporated as variables in the empirical model to account for adaptive capabilities and for potential non-linear relationship between farm characteristics and resilience. The objectives were achieved by adopting and extending the conceptual and analytical frameworks from Lindbloom (2018).

To achieve the first objective, this study utilizes the Resilience Triangle approach method proposed by Bruneau et al. (2003) and used in Lindbloom (2018). To calculate resilience index values for an individual farm i for a shock period j, the *Resilience Triangle* framework is applied to the data obtained from the Kansas Farm Management Association (KFMA), Next, a set of farm characteristics is defined and classified as buffering and adaptive capabilities based on economic theory and practical logical reasoning.

The main findings of the study indicate that the buffering capabilities identified in Lindbloom (2018) are generalizable across an expanded range of shocks. The results also indicate that in addition to diversification, debt-to-asset ratio, and the depreciation ratio serve as a buffering capability for the shocks during the period analyzed. Lastly, the results indicate that the presence of non-linear relationship among debt-to-asset ratio, acre diversification, age of farm operator and farm resilience, implying that certain resources and capabilities can serve as buffering and adaptive capabilities up to a specific threshold.

The limitation of this study is that the proposed method is not able to capture the effect of those farms that have recovered above the point of the initial start of the shock meaning that, the real net farm income per crop acre at the endpoint of shock ($RNFI_{t_E}$) has been set to be equal to the real net farm income per crop acre at the start point of the shock $(RNFI_{t_S})$. This condition has been applied in order to normalize the size of the resilience triangle area. If not doing so, it is possible for some farms to recover and ascend to the initial start point which will create a bigger triangle and a false perception that the farm was not resilient. However, that makes a limitation in computing the true resilience index of the farms which in the end of the shock period had bigger RNFI.

This study extends the existing literature on farm resilience and provides an enhanced conceptual and analytical platform for future studies over extended time periods including COVID-19 and Russia-Ukraine conflict related shocks.

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