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Effect of Diversification on Farm Resilience: Evidence from Kansas

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Abstract
Large drops in net farm income can have a devastating impact on farmers' ability to sustain and recover production volumes. In turn, these drops could send shock waves through the supply chain and multiply the magnitude of value at risk. Although conventional risk management techniques have helped to moderate the impacts of specific sources of risk, they lack the ability to comprehensively cope with uncertainty. The concept of system resilience has emerged to complement conventional risk management options and is defined as the ability of a system to withstand predicted or unpredicted disturbance through development of effective buffering and adaptive capabilities. Researchers have posited that farm diversification is an adaptive capability that can enhance resilience. This study aims to evaluate this assertion by using 47 years of farm-level data from the Kansas Farm Management Association database to calculate a diversification index and a resilience index of a farm i, during time period t, and specify an econometric model to estimate the effect of diversification and other farm characteristics on farm resilience. The contribution of this study to the growing body of literature on agri-food system resilience is threefold. First, it presents the first application of the resilience triangle method at the individual farm level. Second, it provides empirical evidence of the effect of diversification and other farm characteristics on resilience. Third, it highlights potentially fruitful areas for future research on farm resilience.

Keywords: resilience, diversification, production agriculture, Kansas, farm

JEL codes: Q12, Q13, Q19

Introduction

During the three year period from 2014 through 2016, the average U.S. net farm income declined by approximately 56 percent (Featherstone, 2016). This period of decline followed a 96% increase between 2009 and 2013 (USDA – Agricultural Statistics 2021). Although fluctuations in net farm income have not been uncommon over time, this plunge in average farm profitability was one of the most severe drops since the 1980s farm crisis. Risk and uncertainty are generally accepted as inexorable facts of life for agricultural producers. However, large drops in net farm income can have a devastating impact on farmers' ability to sustain and recover production volumes. These factors, in

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turn, could send shock waves through the broader agricultural supply chain – multiplying the magnitude of value at risk.

Although conventional risk management techniques have helped to moderate the impacts of specific sources of risk, they lack the ability to cope comprehensively with uncertainty. The challenges brought by the uncertainties associated with COVID-19, a once-in-a-century global pandemic, and more recently by the Ukraine-Russia war, the most significant armed conflict on the European continent since World War II, have further highlighted the shortcomings of available risk management options in their ability to minimize the effects of environmental, global, and political-legal shocks on agricultural producers and agri-food supply chains.

In an effort to improve how farmers cope with risk and uncertainty, system resilience concepts have started to find applications in research on production agriculture. Agricultural resilience 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. 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 production 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. Rather than attempting to mitigate the potential impacts from specific sources of risk, system resilience is focused on preparing the system to buffer against unexpected shocks and then have the adaptive capabilities to recover in the post-shock environment. Developing resilience, thus, is a continual process in which stakeholders are regularly evaluating their resource allocation decisions.

This study has two broad objectives. The first objective is to establish and compute an index of farm resilience. The second objective is to classify, measure, and compare the resilience-enhancing capabilities of farms. A vital component of any resilient system is the development of buffering capabilities that allow the system to withstand disturbance. Researchers have posited that diversification[5] of farm production is a buffering capability that can enhance the ability to respond to external shocks; in other words, it can strengthen resilience (Featherstone and Moss, 1990; Lin, 2011; Kremen and Miles, 2012). This study aims to test this assertion by using 47 years of farm-level data from the Kansas Farm Management Association database and conducting an empirical examination of the effect of diversification and other farm characteristics on farm resilience to a distinct set of ecological and economic shocks. By applying system resilience theories to production agriculture, a new set of risk management tools becomes available to farmers and policy makers. An improved understanding of the drivers of overall farm resilience can inform management and policy decisions aimed at reducing the magnitude of value at risk from unexpected shocks.

[5] Literature provides varying definitions of farm diversification. Please see Ilbery 1988, Evans and Ilbery 1993 for an extensive discussion.

Methods

The methods utilized in this study involve a conceptual model which applies an existing resilience methodology, 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 (Bruneau et al., 2003; Yang and Xu, 2015). To the authors' knowledge, this study is the first application of the resilience triangle method at the individual farm level. 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) lowest post-shock performance level, and (c) post-recovery performance level. Intuitively, systems with large resilience triangles will have lower levels of resilience (substantial 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). The advantage of this method for measuring system resilience is in its ability to simultaneously capture both the impact of the shock as well as the time to recover. 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. Thus, higher values of the resilience index correspond with more resilient farms.

To achieve the second objective of identifying resilience-enhancing capabilities of farms, and more specifically to measure the impact of farm diversification on resilience, the following conceptual model was proposed:

$$R_i = f([B_i], [A_i], [T_i], [X_i]) \tag{1}$$

where R_i is the resilience index value of the 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 binary variables indicating shock periods, and $[X_i]$ is a vector of the farm-specific characteristics that impact resilience. Because the resilience index values R_i range between zero and one, the fractional logit regression, first introduced by Papke and Wooldridge (1996), was used as an estimation method in the econometric analysis.

Data

The data for this research was obtained from the Kansas Farm Management Association (KFMA). The KFMA data contains detailed, farm-level, financial and production information for farms in Kansas between 1973 and 2020. The data analysis involved five main steps. First, the real net farm income was selected as a specific performance measure to be the basis for computing farm resilience index. This measure is an indicator of past farm resource management decisions and can reflect the impacts of a shock on the fundamental functioning of the system. If real net farm income declines, it will be a result of either an increase in farm expenses, a decrease in value of farm production, or both. The second step was the identification of shock periods that impacted all Kansas farms. To accomplish this step, the statewide average values of real and nominal net farm income per acre for 8,513 KFMA farms were graphed from 1974 through 2020 (Figure 1). The net farm income per acre fluctuated extensively over this period of time. However, there were unique time periods that stood out: the drop in net farm income per acre in 1979, the drop in net farm income per acre in 1998, and the drop

in net farm income per acre in 2015. Consequently, three shock periods selected for the analysis include 1979 - 1988, 1998 - 2004, and 2015 - 2020 periods. To determine whether the 1979, 1998 and 2015 shocks were caused by revenue declines, cost increases, or both, real average value of farm production and real average cash farm expenses (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, auto expense) for 8,513 KFMA farms between 1974 and 2020 was examined in Figure 2. The data indicate that for all three shock periods the drop in average real net farm income was caused by both a decline in the value of farm production and an increase in farm expenses.

Third, the resilience index was calculated for a subsample of farms. The two criteria used for including farms in the analysis are (i) farms that produced crops during three shock periods, and (ii) farms that were operational for the entire duration of each shock period. This resulted in a sample of 1,293[6] units of analysis (farm i during shock t) including 258 farms for shock one, 638 farms for shock two, and 397 farms for shock three. Table 1 presents the summary statistics by region for the farms in each of three shocks across six geographic regions of Kansas: northwest (NW), southwest (SW), north-central (NC), south-central (SC), northeast (NE), and southeast (SE). The resilience index for each farm was calculated using the following formula:

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

Which is the inverse of the area of the triangle resulting from connecting three points, the pre-shock net farm income (NFI_1 at time t_P), the lowest net farm income during the shock (NFI_2 at time t_L), and the net farm income at the end of the shock period (NFI_3 at time t_N). The resilience index is calculated on the individual farm level. While the shock period is based on average farm performance, the reduction in NFI as a result of the shock can happen at various times for each farm. Consequently, the resilience index for each farm is calculated using the period with an initial drop in NFI for that particular farm during (around) each shock period.

Fourth, the diversification index was calculated for each farm as a reflection of buffering capability. The calculation of the diversification index was based on the Herfindahl-Herschman (HH) index (Rhoades, 1993). The diversification index used in the analysis reflects the average of crop-acre diversification levels during the shock periods and was computed as shown in equation (3). 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 (4).

[6] A farm can leave the KFMA database for reasons other than only not surviving economically. They can retire, consolidate, switch to another accountant, etc.

$$D_i^n = \sum_{1}^{20} \left(\frac{TAP_k}{TAP}\right)^2 \tag{3}$$

$$ADiv_i = \left[\sum_{n=t_{P-1}}^{t_{P-3}} D_i^n\right] \times \frac{1}{3} \tag{4}$$

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 include 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 its acres to a single crop, then $D_i = 1$, on the other hand, for a highly diversified farm the value of D_i will be close to zero. To compute the change acre diversification, the difference between $ADiv_i$ and D_i^n was calculated.

Other variables included in the model to reflect buffering capabilities include: the square term of the average acre diversification index ($ADiv_i^2$) to capture the potential nonlinear effect of diversification on resilience, the average debt-to-asset ratio for the three years immediately before the shock (DAR_i) and its square term to capture the effect of debt on the ability to withstand and recover from shocks, the average real value (in $10,000) of beginning crop inventories for the three years prior to the shock ($CropInv_i$) to capture the effect of crop inventory on resilience. The variables reflecting adaptive capabilities include: the change in the level of revenue diversification *(DVR_i)* experienced by farm i from period t_P to t_L, the change in the average level of the crop-acre diversification index ($\Delta ADiv_i$) from the three years prior to time period t_L, and the change in the average operating expense ratio ($\Delta OER_i'$), from the three years prior to the shock to the average operating expense ratio between periods t_P and t_L. These variables reflect the extent of changes on the farm in response to the shock (i.e., extent of adaptation).

The control variables include: the age of the primary operator (Age_i) and the square of the age (Age_i^2), the average size of the farm in acres ($Acre_i$) and its square term ($Acre_i^2$) which is calculated for the duration of the shock, and binary control variables reflecting shock periods ($Time_i$) to capture the effect of differences between shock periods, as well as a set of binary variables to capture the effect of geographic heterogeneity. The fifth and last step of the data analysis was the estimation of the econometric model using the fractional logit estimation method.

Results

Farm Resilience Across Shocks and Regions

Resilience index was computed at the individual farm level, and average values are shown by region in Table 2. These results show that the most resilient regions in the first shock period were the southwest and south-central regions, and the least resilient were the northeast and southeast. For the second shock period, the most resilient regions were the southwest and north-central, and the least resilient regions were the southeast and northeast. For the third shock, the most resilient regions were

the south-central and southwest, while the least resilient were north-central and northeast. Table 2 also shows the percentage of farms recovered from each shock by region. A recovered farm is defined as a farm with post-shock net farm income per acre that was equal or greater than its pre-shock net farm income per acre. For the first shock, the north-central was the region with the highest percentage of recovered farms. For the second and third shock, the southwest region had the highest percentage of recovered farms.

Factors Affecting Farm Resilience

Table 3 presents summary statistics by region for the variables reflecting select buffering and adaptive capabilities. The results of fractional logit estimation are presented in Table 4. Estimations were conducted using farm *i* at shock period *t* as the unit of analysis. Three sample specifications were analyzed: (i) a total sample of 1,293 observations, (ii) a sub-sample of 350 recovered farms only, and (iii) a sub-sample of 943 non-recovered farms only. The first column presents the variable names followed by three sections of parameter estimates and marginal effects for each sample specification with corresponding standard errors presented in parentheses.

The results of the total sample analysis indicate that all variables included in the model to reflect buffering and adaptive capabilities have a statistically-significant effect on resilience. More specifically, the parameter estimate for crop-acre diversification is positive and statistically significant. While the parameter estimate for its square term is negative and statistically significant. Notably, because of the way the diversification index is calculated, the higher values (close to 1) mean less diversified (i.e., more specialized) while lower values (close to 0) mean more diversified. Thus, the results indicate that as diversification increases the resilience will likely decline, but at some level of diversification the effect on resilience turns positive, meaning as diversification increases the resilience increases as well. This implies that on the diversification continuum, farms at the two extremes (i.e., most specialized and most diversified) are likely to be on average more resilient compared to ones in the middle of the continuum.

The parameter estimate for debt-to-asset ratio is negative and statistically significant, while the parameter estimate of its square term is positive and statistically significant. This indicates that as the debt-to-asset ratio increases, the resilience decreases up to some level of debt-to-asset ratio above which the increase in debt-to-asset ratio is associated with an increase in resilience (i.e., inflection in the direction of the effect). This result is counterintuitive because one would expect a linear relationship between debt-to-asset ratio and resilience. The fact that the relationship between debt-to-asset ratio and resilience at the higher end of the debt-to-asset ratio distribution turns positive might be because of other factors that are hard to control in the model. Such factors may include relationships of the farmer and the lender as well as the reputation of the borrower.

The results also indicate a statistically-significant, negative relationship between the value of crop inventory prior to the shock and farms' resilience to the shock. This is likely due to the potential negative effect of the shock on prices, which might not be the case for all shocks. However, the results also indicate that there is no statistically-significant difference in the resilience of farms in the total sample during the second and third shock compared to the first shock period.

The parameter which estimates for variables reflecting farms' adaptive capabilities indicates that the increase in revenue diversification during the shock period is associated with increased farm

resilience. This result is not surprising as the revenue diversification includes revenue from non-farm income and government payments. The results also indicate that farms that reduced their level of diversification during the shock period experienced an increase in resilience. This result is also 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 diversification. The statistically-significant, negative parameter estimate for change in operating expense variable indicates that, on average, farms that managed to reduce their costs during the shock period were able to enhance their resilience to the shock. Regional dummies were included for northwest, southwest, north-central, south-central, and northeast regions with southeast omitted to serve as a comparison group. The results of estimation suggest that farms in northwest and southwest regions were more resilient than farms in southeast, while the farms in northeast were less resilient than those in southeast.

The estimation results from the sub-samples of recovered and unrecovered farms are largely consistent with the results based on total sample. One notable difference is that for the sample of recovered farms only, the age has a statistically-significant, non-linear effect. This implies that the farm resilience declines with an increase in operator's age up to a certain age, after which the effect of age on resilience turns positive. This is likely due to higher flexibility and adaptability of farm operators at the lower end of the age distribution and relatively higher economies of learning and experience at the higher end of the age distribution of farm operators.

Conclusions

The challenges brought by the uncertainties associated with global pandemic and geopolitical tensions have further highlighted the shortcomings of available risk management options in their ability to minimize the effects of environmental, global, and political-legal shocks on agricultural producers and agri-food supply chains. To help improve farmers' ability to cope with risk and uncertainty, system resilience concepts have started to find applications in research on production agriculture. Rather than attempting to mitigate the potential impacts from specific sources of risk, system resilience is focused on preparing the system to buffer against unexpected shocks and then have the adaptive capabilities to recover in the post-shock environment. The purpose of this study is to improve the understanding of farm resilience and the effect of diversification and other farm-level characteristics on resilience as buffering and adaptive capabilities. An improved understanding of the drivers of overall farm resilience can inform management and policy decisions aimed at reducing the magnitude of value at risk from unexpected shocks.

The methods involve an application of the resilience triangle approach and the analysis of unique, 47-year panel data on Kansas farms. The analysis involves calculation of the resilience index for each farm across three distinct shock periods, and the econometric estimation of the effect of diversification, financial leverage, inventory, and other farm characteristics. The results indicate that the crop-acre diversification and debt-to-asset ratio have a non-linear effect on resilience. This implies that up to a certain threshold, diversification and financial leverage can serve as effective buffering capabilities against shocks. The results also indicate that the ability of farms to increase revenue diversification, shed less profitable activities, and manage down the costs can serve as indication of strong adaptive capabilities for enhancing resilience. Potential directions for further research to build on the findings of this study can include examination and comparison of resilience-enhancing capabilities across specific shocks, as well as studying farms that not only recovered to the pre-shock

performance levels, but also surpassed it. Thus, revealing the effects of potential transformative capabilities in addition to buffering and adaptive capabilities. The contribution of this study to the growing body of literature on agri-food system resilience is threefold. First, it presents the first application of the resilience triangle method at the individual farm level. Second, it provides empirical evidence of the effect of diversification and other farm characteristics on resilience. Third, it highlights potentially fruitful areas for future research on farm resilience.

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Figure 1: Average Value of Real and Nominal Net Farm Income for 1974-2020 in Kansas; U.S. Census Bureau Producer Price Index (Base year = 1982:84)

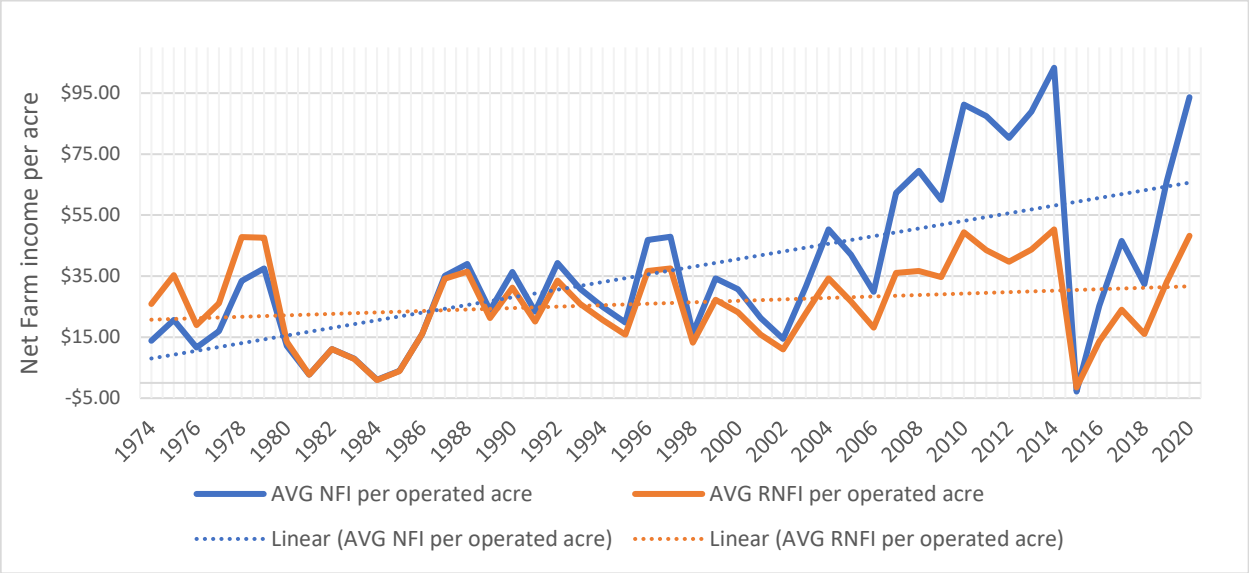

Figure 2: Statewide Averages of the Value of Farm Production and Cash Farm Expenditures for 1974-2020 in Kansas

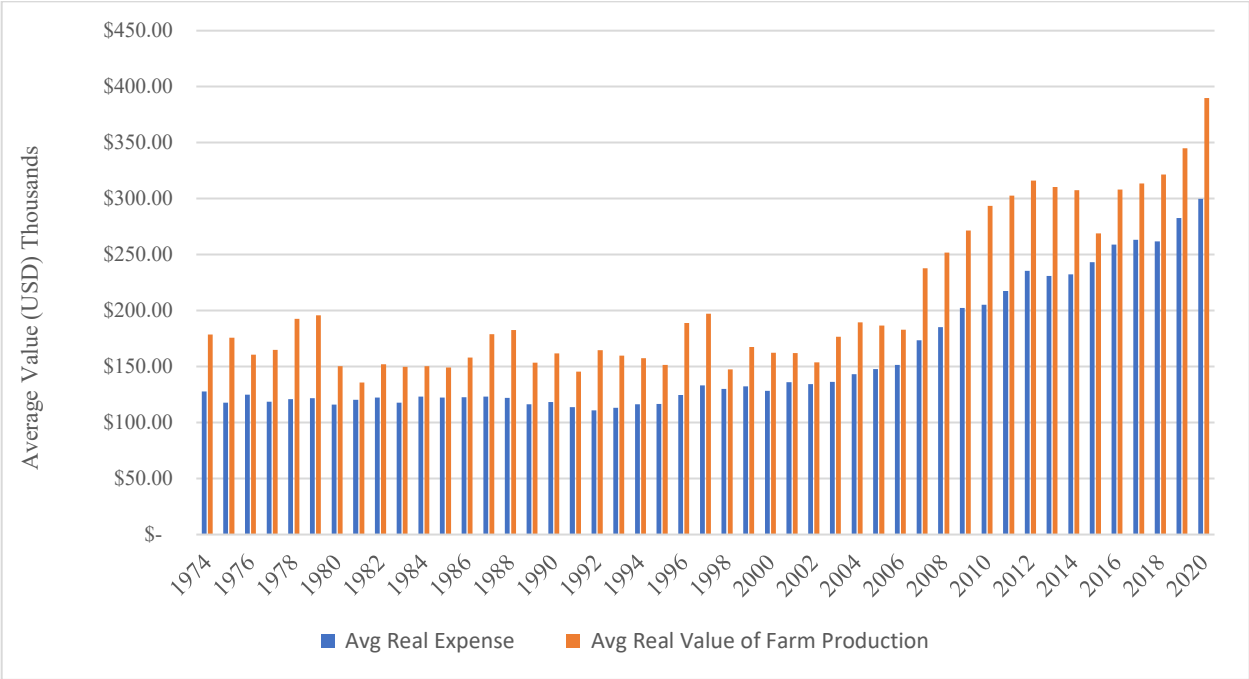

Table 1: Summary Statistics by Geographic Region

	Northwest	Southwest	North-central	South-central	Northeast
First Shock Period					
Number of Observations	18	34	31	63	44
Avg. Age	47	52	48	48	48
Avg. Acres Operated	2727	2318	1218	1216	1391
Crop-Only Farms	39%	76%	55%	78%	64%
Diversified Farms	61%	24%	45%	22%	36%
Avg. Real NFI	$6,249	$10,342	$7,676	$18,307	$23,946
Avg. Real NFI / Acre	$4.83	$6.83	$9.54	$21.17	$49.94
Avg. Real NFI *	$5,524	$6,678	$7,134	$16,663	$23,052
Avg. Real NFI / Acre *	$4.04	$4.65	$8.49	$19.17	$48.23
Second Shock Period					
Number of Observations	38	34	111	139	108
Avg. Age	49	54	50	51	52
Avg Acres Operated	2792	2383	1607	1767	1554
Crop-Only Farms	82%	97%	77%	94%	79%
Diversified Farms	18%	3%	23%	6%	21%
Avg. Real NFI	$29,252	$16,247	$13,535	$23,860	$34,135
Avg. Real NFI / Acre	$21	$13	$13	$19	$34
Avg. Real NFI *	$12,743	$(1,170.33)	$5,629	$11,671	$24,866
Avg. Real NFI / Acre *	$10	$2	$5	$10	$25
Third Shock Period					
Number of Observations	31	8	125	40	92
Avg. Age	56	66	58	60	60
Avg. Acres Operated	4569	2508	2073	2285	1550
Crop-Only Farms	81%	88%	82%	98%	84%
Diversified Farms	19%	13%	18%	3%	16%
Avg. Real NFI	$130,740	$74,511	$65,107	$100,882	$76,264
Avg. Real NFI / Acre	$47	$32	$55	$57	$62
Avg. Real NFI *	$109,573	$56,337	$56,125	$89,230	$69,062
Avg. Real NFI / Acre *	$40.14	$24.55	$47.84	$50.40	$55.40

** Government payments are excluded*

Table 2: Average Resilience Index (R) Values by Region (Index values are multiplied by 100)

	Northwest	Southwest	North-central	South-central	Northeast	Southeast
Avg. R 1st Shock	0.626	1.486	0.892	1.326	0.509	0.506
% Recovered farms	33%	41%	45%	43%	39%	43%
Avg. R 2nd Shock	1.071	1.233	1.158	1.035	0.362	0.699
% Recovered farms	24%	26%	20%	22%	23%	19%
Avg. R 3rd Shock	1.645	2.681	0.716	2.159	0.621	0.875
% Recovered farms	45%	75%	21%	30%	24%	27%

Table 3: Summary Statistics of Variables Reflecting Farm Characteristics

Capabilities Variables	Northwest	Southwest	North-central	South-central	Northeast	Southeast
First Shock Period						
3-yr. Debt to Asset Ratio	38%	31%	27%	37%	25%	27%
3-yr. Acre Divr.	0.559	0.522	0.377	0.469	0.302	0.361
3-yr. Crop Inventory $	$68,151	$90,866	$35,700	$40,187	$53,553	$58,329
Chg. Rev. Divr.	0.175	0.189	0.243	0.148	0.111	0.117
Chg. Acre Divr.	-0.088	-0.069	-0.007	-0.005	-0.026	-0.013
Chg. Expense Ratio	-0.162	-0.103	-0.070	-0.100	-0.045	-0.028
Second Shock Period						
3-yr. Debt to Asset Ratio	33%	29%	37%	31%	24%	29%
3-yr. Acre Divr.	0.418	0.480	0.358	0.466	0.327	0.372
3-yr. Crop Inventory $	$92,971	$79,388	$41,199	$54,670	$74,318	$76,933
Chg. Rev. Divr.	-0.078	-0.156	-0.022	-0.120	0.024	-0.018
Chg. Acre Divr.	-0.046	-0.028	-0.031	-0.045	0.004	-0.023
Chg. Expense Ratio	0.056	0.017	0.075	0.051	0.126	0.086
Third Shock Period						
3-yr. Debt to Asset Ratio	17%	11%	18%	11%	16%	22%
3-yr. Acre Divr.	0.354	0.435	0.295	0.414	0.383	0.382
3-yr. Crop Inventory $	$226,682	$164,454	$109,903	$140,918	$138,153	$153,923
Chg. Rev. Divr.	-0.033	0.025	-0.082	-0.130	-0.059	-0.027
Chg. Acre Divr.	0.001	-0.025	-0.014	-0.031	0.015	0.029
Chg. Expense Ratio	0.063	0.026	0.044	0.066	0.073	0.041

Table 4: Results of Fractional Logit Estimation

	Total Sample		Recovered Farms		Non-Recovered Farms	
R index	Coef.	Marginal Effect	Coef.	Marginal Effect	Coef.	Marginal Effect
3-yr. Debt-to-Asset Ratio	-0.9700**	-0.0086*	-0.5515	-0.0053	-1.3584**	-0.0117*
	(0.4641)	(0.0045)	(0.3611)	(0.0034)	-0.6542	(0.0065)
Sq. 3-yr. Debt-to-Asset Ratio	0.2327**	0.0021**	0.2769***	0.0027***	0.2706**	0.0023*
	(0.1057)	(0.0010)	(0.0961)	(0.0009)	(0.1339)	(0.0013)
3-yr. Acre Diversification	6.1074***	0.0542**	5.5798***	0.0534***	7.9224***	0.0682**
	(2.2994)	(0.0236)	(1.9020)	(0.0200)	(3.0018)	(0.0314)
Sq. 3-yr. Acre Diversification	-4.0402**	-0.0359*	-4.1097**	-0.0394**	-5.1893**	-0.04468*
	(1.8434)	(0.0184)	(1.6565)	(0.0170)	(2.5184)	(0.0253)
3-yr. Crop Inventory (10,000$)	-0.0182**	-0.0002*	0.0314***	-0.0003**	-0.0234*	-0.0002
	(0.0091)	(0.0001)	(0.0114)	(0.0001)	(0.0137)	(0.0001)
Chg. Rev. Diversification	-0.1587	-0.0014	-0.1389	-0.0013	-0.4977*	-0.0043*
	(0.1187)	(0.0011)	(0.1098)	(0.0011)	(0.2567)	(0.0024)
Chg. Acre Diversification	3.4636**	0.0307**	0.6589	0.0063	4.0456**	0.0348**
	(1.5679)	(0.0151)	(1.1272)	(0.0107)	(1.7216)	(0.0162)
Chg. Expense Ratio	-1.4835*	-0.0132	-1.4639*	-0.0140*	-1.7620*	-0.0152
	(0.8642)	(0.0081)	(0.8064)	(0.0078)	(1.0470)	(0.0098)
Age	-0.0276	-0.0002	-0.1679**	-0.0016**	0.0104	0.0001
	(0.0339)	(0.0003)	(0.0698)	(0.0007)	(0.0423)	(0.0004)
Sq. Age	0.0002	0.0000	0.0015**	0.0000**	-0.0001	-0.0000
	(0.0004)	(0.0000)	(0.0006)	(0.0000)	(0.0005)	(0.0000)
Average Acre	0.0001	0.0000	0.0003**	0.0000**	0.0000	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)
Northwest						

	0.4919**	0.0044**	-	-	-	-
	(0.2023)	(0.0018)	-	-	-	-
Southwest	0.5951**	0.0053**	-	-	-	-
	(0.2927)	(0.0026)	-	-	-	-
North-central	0.3631	0.0032	-	-	-	-
	(0.2927)	(0.0023)	-	-	-	-
South-central	0.4815	0.0043	-	-	-	-
	(0.3265)	(0.0030)	-	-	-	-
Northeast	-0.3515	-0.0031**	-	-	-	-
	(0.1587)	(0.0015)	-	-	-	-
Shock 2	0.2545	0.0021	-0.2238	-0.0021	0.4358	0.0038
	(0.2591)	(0.0023)	(0.2469)	(0.0024)	(0.3130)	(0.0029)
Shock 3	0.4824	0.0034	0.6381***	0.00611**	0.3650	0.0031
	(0.3043)	(0.0024)	(0.2484)	(0.0025)	(0.3791)	(0.0034)
Constant	-5.7633***		-1.7303		-7.2521***	
	(1.0377)		(1.6089)		(1.3183)	

In parentheses presented Robust Standard Errors for Coefficients and Standard Error for Marginal Effect calculated using Delta Methods.