Explaining Share of Farm Loss Systemic with County Loss in the United States?

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Abstract

Purpose - Relationship between farm and county losses determines whether the county program provides too little, too much, or similar amount of assistance relative to the loss on an individual farm. A review of the literature finds limited analysis of the determinants of this relationship. This paper conducts such an analysis using farm-level yield data.

Research design, data, and methodology - Farm-level yield data from Illinois and Kansas farm business management associations are used for to calculate the correlation between farm and county loss and the share of farm loss systemic with county loss, and also for the regression analysis.

Results - Average share of farm loss systemic with the county loss lies between 42% and 68%. The correlation between farm and county yield/revenue deviation from expected value is statistically significant in all four models. The coefficient is positive, implying the higher the correlation, the larger the share of farm loss that is systemic with the county loss.

Conclusions - The findings of this study are consistent with the existing literature which argues that county variability may not be closely associated with farm variability. The findings of this study thus raise questions about the efficacy of area yield and revenue insurance products in helping farmers manage their risk.

Keywords: Agricultural Risk Coverage, Agribusiness, Agricultural Marketing, County Loss, Systemic Loss.

JEL Classifications: Q13, Q18.

1. Introduction

He Agricultural Act of 2014 shifted the U.S. crop safety net toward providing protection against losses. Among the new loss assistance programs are two that cover risk at the county level: Agricultural Risk Coverage – County(ARC-CO) and Supplemental Coverage Option(SCO). A key factor in assessing these programs is the relationship between farm and county losses. This relationship determines whether the county program provides too little, too much, or similar amount of assistance relative to the loss on an individual farm. A review of the literature finds limited analysis of the determinants of this relationship. This paper conducts such an analysis using farm-level yield data from the Illinois and Kansas farm business management associations.

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2. Literature Review

A historically important public policy issue for crop insurance has been whether it should be written at the county or farm level(Halcrow, 1949). Miranda(1991) extended Halcrow's proposal for area yield insurance by decomposing an individual farm's total yield risk into a component systemic with county yield risk and a component idiosyncratic to individual farm risk. His analysis suggested that area yield insurance with a low deductible can provide better protection against yield loss than individual yield insurance. As both Halcrow and Miranda note, a key motivation for using county yield is the presence of adverse selection resulting from farmers knowing more about their production risk than insurers. This asymmetric information results in farmers who purchase insurance being more likely to receive an insurance indemnity payment(Bourgeon & Chambers, 2003). Halcrow and Miranda also note that individual-yield crop insurance is also associated with high administrative costs due to the need to assess and monitor individual farm data.

On the other hand, a number of papers argue that county variability may not be closely associated with farm variability.

Claassen and Just(2011) finds some characteristics of farm-level data were lost when county data was used. This finding held across crops and regions, raising the concern about using county-level data for individual farm insurance. They used county-level yield data from the US National Agricultural and Statistical Service(NASS) to characterize county and farm level yield data. Yield variation was decomposed into systemic and random variation by using a detrending method that adapted non-parametric estimate of county trends to the farm level.

Barnett et al.(2005) argues that the area yield insurance contract can cause a significant yield loss to a farm with an idiosyncratic event while no indemnity is triggered at the county yield level. They compared area and individual crop insurance programs that are provided by FCIP(The Federal Crop Insurance Program) using farm-level yield data across multiple states for the corn and sugar beet farms. They assessed the performance of two types of insurances on how much they can reduce the variability of net yield. As a result, they found that area yield insurance program reduced risk pretty well in relatively homogeneous states, but did not performed well in the states with low correlation between county and farm yields.

Gerlt, Thompson, and Miller(2014) concludes that using county data for estimating crop insurance premiums may be biased while rising coverage tends to reduce the bias. Considering the difficulty of applying county yield with farm yield distribution, they used simulation experiments with some mathematical derivations to exploit the fact that county yields are aggregated farm yields to draw the relation between county and farm yields.

Cooper et al.(2012) finds Risk Management Agency (RMA) insurance premiums were significantly mispriced compared to premiums generated using the farm's observed yield variation. They simulated a stylized version of the methods used by RMA to price individual farm insurance. Their individual farm yield data were from the Illinois and Kansas farm management associations while county yield data were from NASS.

3. Methodology

This study investigates the factors that can explain the share of farm loss that is systemic with the county. A specific focus is the role of the correlation between deviations in farm yield and county yield. Correlation is examined because it is commonly used when discussing risk management and insurance with practitioners, as well as when analyzing individual behavior(Kim & Youn, 2015). However, it is important to keep in mind that it is well-documented in the academic literature that linear correlation has limits when variables have tail dependence (Joe, 1997; Cherubini et al., 2004; Nelsen, 2006). Specifically, random variables exhibit a higher correlation during bad events(e.g., bad weather) than during good events(Patton, 2007). As a result, the "copula method" has gained currency in academic research.

3.1. Data and Calculation of Variables

Data for this analysis are from the Illinois Farm Business Farm Management(FBFM) program and Kansas Farm Management Association(KFMA). FBFM is a farmer-owned cooperative that has a working relationship with the University of Illinois at Urbana-Champaign. Members maintain production and financial records for their farms. At the end of a calendar year, financial statements and production records are prepared and aggregate databases of crop and livestock production, receipts, expenses, inventories, and capital accounts are produced to develop benchmarks against which farmers can compare their farms. To be in the database, FBFM personnel must certify a farm's data are reliable and usable. KFMA data are developed in a similar manner(Langemeier, 2005).

Consistent preparation of farm level data, including yields, begins with 1972 for FBFM and 1973 for KFMA. Yields were available through the 2012-13 crop year when this study was begun. Because FBFM and KFMA report yields on a per planted acre basis, per planted acre yields were calculated for the county. County yield data were from USDA(United States Department of Agriculture), NASS (National Agricultural Statistical Service) Quick Stats program. For soybeans and wheat, planted yield for a county is calculated by dividing total production by acres planted in the county. Acres planted to corn can be harvested for grain or silage. USDA, NASS reported corn acres harvested for silage for some Kansas counties. Counties with no reported acres of corn harvested for silage either had no acres harvested for silage in the county or USDA could not release

<Table 1> Data Source and Description

	Data Source	Website	Number of Observations	
Kansas	Kansas Farm Management Association	https://www.agmanager.info/kfma	Soybeans	28
			Wheat	35
Illinois	Illinois Farm Business Farm Management	https://www.fbfm.org/	Corn	61
			Soybeans	61

Source: Own

harvested silage acres without potentially revealing information about an individual farm. The latter situation likely means silage acres are a small share of corn acres in the county. It was decided that, when available, harvested silage acres would be subtracted from planted acres. This decision implies that all non-harvested acres were assumed to be intended for harvest as grain. While non-harvested acres could have been intended for silage, acres with production stress are more likely to be harvested for silage than for grain because silage uses most of the plant, not just the grain.

To provide a sensitivity check, expected farm/county yield is estimated use using two methods: a 5-year Olympic moving average (OMA5) and a linear trend-line (TLY) fitted to the farm/county yield data. OMA5 is used to compute the yield benchmark by the Average Crop Revenue Election (ACRE) program in the Food, Conservation, and Energy Act of 2008 and the yield and price benchmarks in the Agricultural Risk Coverage (ARC) program in the Agricultural Act of 2014. The trend-line estimate is a within sample estimate that incorporates the increasing yield trend observed over the analysis period.

The OMA5Y and TLY are calculated as:

$$(1) \quad \mathbf{OMA5Y}_t = \frac{\left\{\sum_{s=1}^{5} \mathbf{AY}_{(t-s)} - \mathbf{MAX}\left[\{\mathbf{AY}_{(t-s)}\}_{s=1}^{5}\right] - \mathbf{MIN}\left[\{\mathbf{AY}_{(t-s)}\}_{s=1}^{5}\right]\right\}}{3}$$

$$(2) \quad \mathbf{TLY}_t = \widehat{\alpha}_{\mathrm{OLS}} + \widehat{\beta}_{\mathrm{OLS}} \times t$$

$$\text{where} \quad (\widehat{\alpha}_{\mathrm{OLS}}, \quad \widehat{\beta}_{\mathrm{OLS}}) = \mathrm{argmin}\{\sum_{t=1978}^{2012}(\mathbf{AY}_t - \alpha - \beta \times t)^2\}$$

where AY = actual yield and t = 1978, 1979, ..., 2012. Depending on whether the actual yield is for farms (AFY) or for counties (ACY), OMA5Y and TLY respectively becomes OMA5FY and TLFY for farms and OMA5CY and TLCY for counties.

For state-crop combination k and crop year t, crop yield loss for farm i (FYL) and county j (CYL) based on the 5-year Olympic moving average are calculated, respectively:

$$(3) \quad \mathrm{FYL}_{ikt} = \mathrm{MAX}[\{(\alpha \times \mathrm{OMA5Y}_{ikt}) - \mathrm{AY}_{ikt}\}, \ 0]$$

$$(4) \quad \mathrm{CYL}_{jkt} = \mathrm{MAX}[\{(\alpha \times \mathrm{OMA5Y}_{jkt}) - \mathrm{AY}_{jkt}\}, \ 0]$$

where α is analogous to the insurance deductible. Varying α allows the behavior of the share of farm loss systemic with a larger geographical area to be examined at different levels of loss. Share of farm loss systemic with county loss could differ, for example, for deductibles of 10% and 30%. Crop loss based on the trend-line method, designated FYL and CYL are calculated by replacing OMA5Y in equations (3) and (4) with TLY.A similar analysis is conducted for

revenue utilizing the crop insurance prices determined prior to planting and at harvest. Specifically, for crop k and crop year t, crop revenue loss for farm I (FRL) and county j (CRL) are calculated as follows based on the 5-year Olympic moving average:

$$(5) \quad \mathrm{FRL}_{ikt} = \mathrm{MAX}[\{(\alpha \times \mathrm{OMA5Y}_{ikt} \times \mathrm{PIP}_t) - (\mathrm{AY}_{ikt} \times \mathrm{HIP}_t)\}, \ 0]$$

$$(6) \quad \mathrm{CRL}_{jkt} = \mathrm{MAX}[\{(\alpha \times \mathrm{OMA5Y}_{jkt} \times \mathrm{PIP}_t) - (\mathrm{AY}_{jkt} \times \mathrm{HIP}_t)\}, \ 0]$$

where PIP = insurance price prior to planting and HIP = harvest insurance price. FRL and CRL based on the trend-line method, are calculated by replacing OMA5Y with TLY in equations (5) and (6).

Share of farm i's per acre yield loss systemic with per acre yield loss of county j in which farm i is located (SYL) is calculated for crop k and crop year t as follows:

$$(7) \quad \mathrm{SYL}_{ijkt} = \mathrm{MIN}[\mathrm{FYL}_{ikt}, \ \mathrm{CYL}_{jkt}] \ / \ \mathrm{FYL}_{ikt}$$

$$(8) \quad \mathrm{SRL}_{ijkt} = \mathrm{MIN}[\mathrm{FRL}_{ikt}, \ \mathrm{CRL}_{jkt}] \ / \ \mathrm{FRL}_{ikt}$$

If the farm's loss exceeds its county's loss, share of farm loss systemic with the county is less than 100%. If the farm's loss is less than or equal to its county loss, then 100% of the farm's loss is systemic with its county's loss. The average share of a farm's loss that was systemic with the county was computed by averaging the shares for the years that the farm experienced a loss.

Share of farm loss systemic with its county loss is estimated for three combinations of farm and county losses. They are: 1) 0 percent farm loss and 0 percent county loss, 2) 15 percent farm loss and 10 percent county loss, and 3) 15 percent farm loss and 15 percent county loss. These combinations allow for a sensitivity check of results under different farm and county loss levels. The first combination covers all losses on the farm. The second combination reflects the smallest deductible associated with individual farm and county insurance, respectively. The third combination is the highest deductible loss observed across all farm observations.

For crop k, the correlation between yield deviations on farm i and county j in which farm i is located, denoted by X1, is calculated:

$$(9) \quad \mathrm{X1}_{ijk} = \mathrm{Corr}(\mathrm{AY}_{ikt} \ / \ \mathrm{5OMAY}_{ikt}, \ \mathrm{AY}_{jkt} \ / \ \mathrm{5OMAY}_{jkt})$$

Similarly, the correlation between revenue deviations of farm i and county j in which farm i is located, denoted by X2, is calculated:

$$(10) \quad \mathrm{X2}_{ijk} = \mathrm{Corr}[\{(\mathrm{AY}_{ikt} \times \mathrm{HIP}_t) \ / \ (\mathrm{5OMAY}_{ikt} \times \mathrm{PIP}_t)\},$$
$$\{(\mathrm{AY}_{jkt} \times \mathrm{HIP}_t) \ / \ (\mathrm{5OMAY}_{jkt} \times \mathrm{PIP}_t)\}]$$

The correlation was calculated using all years, including years in which the no loss occurred on the farm. A

correlation was also calculated only using years in which a loss occurred. Results of the two correlation analyses were similar and thus not presented.

Besides the correlation between farm and county deviations, 4 other independent variables are included in the model: (1) average ratio of farm yield or revenue to county yield or revenue, (2) ratio of the standard deviation of farm yield or revenue to the standard deviation of county yield or revenue, (3) size of county, and (4) number of acres planted to the crop on the farm. The first two variables are characteristics of the farm and county that are related to losses in crop insurance(Cooper et al., 2012). The size of the county is included because it is possible that, ceteris paribus, the correlation between farm and county loss may be less a farm of a given size is a smaller share of larger than smaller county. Size of county is measured in square miles and is available from the website of the National Association of Counties. Number of acres planted to the crop on the farm was measured in acres and was available from the farm management association data set. This variable was included since yield variability declines as acres planted to the crop on the farm increases (Marra & Schurle, 1974; Knight et al., 2010).

3.2. Estimation Framework

Farms elect whether or not to participate in the annual collection of data by the farm management associations. For this reason and because farms go out of business for a variety of reasons, only a few farms have a complete set of data for the observation period. In addition, availability of county yields becomes more problematic later in the analysis period, especially for Kansas. A number of farms were eliminated from the analysis not because of missing data for the farm, but because of missing data for the county in

which the farm was located. Given these data constraints, it was necessary to include farms with one missing observation to obtain a sufficient number of observations. Even after adding these farms, only four state-crop combinations had more than 20 observations: Illinois-corn, Illinois-soybeans, Kansas-soybeans, and Kansas-wheat. The number of observations are 61 for Illinois corn, 61 for Illinois soybeans, 28 for Kansas soybeans, and 35 for Kansas wheat.

Given the relatively small number of farms for each state-crop combination and unbalanced panel structure, a pooled model, not a fixed effect model(Lee & Lee, 2017), is estimated for both yield(equation 8) and revenue(equation 9) loss(Erum et al., 2016):

$$(11)\ Y1_{ijk} = \alpha_0 + \alpha_1 X1_{ijk} + \alpha_2 AR_{ijk} + \alpha_3 SDR_{ijk} + \alpha_4 CS_{jk} + \alpha_5 PA_{ijk} + K\beta + K{\times}X1_{ijk}{\times}\gamma + \varepsilon_{ijk}$$

$$(12)\ Y2_{ijk} = \theta_0 + \theta_1 X2_{ijk} + \theta_2 AR_{ijk} + \theta_3 SDR_{ijk} + \theta_4 CS_{jk} + \theta_5 PA_{ijk} + K\omega + K{\times}X2_{ijk}{\times}\eta + v_{ijk}$$

where i = subscript for farm, j = subscript for county, k = subscript for crop, AR = average farm to county yield or revenue ratio, SDR = farm to county yield or revenue standard deviation ratio, CS = county size, PA = acres planted to crop on the farm, K = three dummy variables for four state-crop combinations where Illinois corn is the base category, (α, β, γ, θ, ω, η) are parameters to estimate, and (ε, v) are error terms. Dummy variables, K, capture the heterogeneity of Y by state-crop combination. Interaction terms of K with X capture the heterogeneity in the impact of X on Y by state-crop combination. Due to the potential violation of the Gauss-Markov assumptions on (ε, v), the Feasible Generalized Least Squares (FGLS) technique is used to achieve efficiency in estimation.

<Table 2> Correlation between Percent Deviation of Farm and County Yield and Revenue from the Expected Value with Expected Yield Calculated as a 5-Year Olympic Moving Average

Deviation by State-Crop Combination	Mean	Standard Deviation	Minimum	Maximum
Yield Deviation[A]				
Illinois Corn	0.84	0.09	0.55	0.96
Illinois Soybeans	0.74	0.11	0.49	0.92
Kansas Soybeans	0.84	0.07	0.62	0.92
Kansas Wheat	0.78	0.12	0.38	0.95
All Observations	0.79	0.11	0.38	0.96
Revenue Deviation[B]				
Illinois Corn	0.79	0.16	0.15	0.95
Illinois Soybeans	0.82	0.13	0.37	0.96
Kansas Soybeans	0.85	0.08	0.57	0.94
Kansas Wheat	0.78	0.12	0.39	0.96
All Observations	0.81	0.13	0.15	0.96

Note: A. For both farm and county yield for year t percent deviation is calculated as actual yield divided by expected yield. B. For both farm and county revenue, for year t percent deviation is calculated as ((pre-plant insurance revenue for year t) / (harvest insurance revenue for year t)).

Source: Original calculations using data from Illinois Farm Business Farm Management (FBFM) program, Kansas Farm Management Association (KFMA), and U.S. Department of Agriculture, National Agricultural Statistical Service.

<Table 3> Share of Farm Loss Systemic with Yield Loss at Alternative Loss Levels for Yield and Revenue, Expected Yield Calculated Using a 5-Year Olympic Moving Average

	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Measure by State-Crop Combination	Farm 0% County 0%				Farm 10% County 10%				Farm 15% County 15%			
Yield												
Illinois Corn	0.64	0.12	0.3	0.84	0.63	0.18	0.14	0.96	0.63	0.21	0	1
Illinois Soybeans	0.51	0.11	0.21	0.79	0.45	0.16	0.11	0.82	0.42	0.2	0	0.8
Kansas Soybeans	0.65	0.08	0.53	0.81	0.6	0.1	0.42	0.79	0.58	0.11	0.33	0.81
Kansas Wheat	0.57	0.09	0.4	0.71	0.54	0.12	0.3	0.76	0.54	0.14	0.27	0.83
All Observations	0.58	0.12	0.21	0.84	0.55	0.17	0.11	0.96	0.54	0.2	0	1
Revenue												
Illinois Corn	0.65	0.11	0.38	0.83	0.52	0.15	0.17	0.8	0.44	0.17	0.1	0.76
Illinois Soybeans	0.61	0.12	0.34	0.85	0.52	0.18	0.09	0.82	0.48	0.22	0.06	0.94
Kansas Soybeans	0.68	0.07	0.54	0.82	0.65	0.08	0.48	0.8	0.62	0.09	0.43	0.79
Kansas Wheat	0.59	0.11	0.39	0.84	0.53	0.13	0.28	0.82	0.52	0.15	0.25	0.81
All Observations	0.63	0.11	0.34	0.85	0.54	0.16	0.09	0.82	0.49	0.18	0.06	0.94

Source: Original calculations using data from Illinois Farm Business Farm Management (FBFM) program, Kansas Farm Management Association (KFMA), and U.S. Department of Agriculture, National Agricultural Statistical Service.

Two regression equations were estimated. One had the correlation and state-crop dummy variables as independent variations. The second added the dummy variables, average farm-county yield or revenue ratio, farm-county yield or revenue standard deviation ratio, size of county, and number of acres planted to the crop on the farm. The first examines the role of the correlation variables within the context of potential differences across crop and states in the agro-climate production environment. The second model examines the explanatory power of correlation when other explanatory variables identified in the literature are included. In this model, the explanatory power of correlation is conditioned on the other explanatory variables.

4. Results

The results of the analysis varied little when expected yield was calculated using a 5-year Olympic moving average or a linear trend-line. Therefore, to conserve space and focus the discussion, only the results from the analysis using the 5-year Olympic moving average are discussed. Results from the linear trend-line analysis are available from the authors.

Descriptive statistics of the correlations between farm and county percent deviations from the 5-year Olympic moving average are generally similar for yield and revenue deviations and across the different state-crop combinations (see <Table 2>). The average correlation for a state-crop combination for yield deviation ranges from +0.74 for Illinois soybeans to +0.84 for Illinois corn and Kansas soybeans and ranges for revenue deviation from +0.78 for Kansas wheat to +0.85 for Kansas soybeans. Standard deviations of the correlations range from .07 for yield deviation of Kansas

soybeans to 0.16 for revenue deviation of Illinois corn. The maximum correlation for each state-crop combination exceeds +0.96. Even though the minimum correlation exhibits the largest variation across the different variables and ranges as low as 0.15 for revenue deviation of Illinois corn, 90% of the correlations across all state-crop combinations exceed 0.64 for yield deviation and 0.65 for revenue deviation. Thus, in general the correlations between farm and county deviations from the 5-year Olympic moving average were high for most farms.

Average share of farm loss systemic with the county loss lies between 42% and 68%(see <Table 3>). The former is for Illinois soybean yield at 15% farm and county deductible while the latter is for Kansas soybean revenue at 0% farm and county deductible. The systemic share tends to decline as the deductible increases, but magnitude of the decline varies across state-crop and deductible combination. The decline is greater for revenue, with the share of farm revenue systemic loss averaging 49% for the 15% deductible combination compared to 63% for the 0% deductible combinations across the four state-crop combinations. Smallest range for the share of farm loss systemic with the county is 0.28 for Kansas soybeans for both yield and revenue loss at the 0% farm and county deductible(see <Table 3>). Largest range is 1.0 for Illinois corn revenue loss at the 15% farm and county deductible.

Descriptive statistics for the other variables included in the regression analysis are reported in <Table 4>. On average, the farms included in this analysis had higher yields and revenue than their county. This finding is not unexpected since the farms have survived since the early 1970s. One possible reason for their survival could be consistently higher yields. The farms in this study also had a higher standard deviation of yield and revenue variation than their county.

The relative farm-to-county ratio was roughly of the same order of magnitude for both yield/revenue and the standard deviation of yield/revenue.

Average size of county is roughly the same for each state-crop combination. Moreover, the largest county was three to five times larger than the smallest county for each state-crop combination. Average acres planted to a crop in a year by the farms in the study was nearly the same for Illinois corn, Illinois soybeans, and Kansas soybeans, but over 100 acres more for Kansas wheat. Considerable variation existed for a given state-crop combination in the average annual number of acres planted to a crop across the farms in the study.

Regression analysis was conducted for each of the three deductible combinations. Because the results are similar for the three analyses, only the results for the 15% farm and county deductible are discussed. The regression results for the other two deductible combinations are available from the authors. Furthermore, the truncated dependent variable model, Tobit model, was also estimated as the dependent variable is truncated at zero and 100. However, since only a few of the dependent variables were numerically close to the truncated values, the results were almost identical to those derived from the simple linear regression.

The correlation between farm and county yield/revenue deviation from expected value is significant with 99%

statistical confidence in all four models(see <Table 5>). The coefficient is positive, implying that, as expected, the higher the correlation, the larger the share of farm loss that is systemic with the county loss. Including only correlation with the fixed effects variables of crop and state in the regression equations resulted in R^2s of 0.37 for yield and 0.44 for revenue. Thus, even though correlation is statistically significant, it does not explain a large share of a farm's systemic loss with the county either for yield or revenue.

The R-squared improves with the addition of the other variables, especially for the yield model. However, approximately half the variation in the share of farm loss systemic with the county remains unexplained. Besides the correlation of farm and county variation, the only other variable statistically significant in both the yield and revenue models is the ratio of farm to county standard deviations. It is significant with 99% statistical confidence in the yield model and with 95% statistical confidence in the revenue model. Both coefficients are negative, indicating that the greater is the variation in farm yield / revenue relative to county yield / revenue, the smaller is the share of farm loss that is systemic with county loss. In other words, the greater is the variability of yield / revenue for a farm relative to the variability of county yield / revenue, the greater is the share of the farm's loss unique to that farm.

<Table 4> Descriptive Statistics for Other Independent Variables in Regression Analysis

	Mean	Standard Deviation	Minimum	Maximum
Annual Ratio of Farm Yield to County Yield				
Illinois Corn	1.08	0.09	0.77	1.24
Illinois Soybeans	1.12	0.11	0.73	1.37
Kansas Soybeans	1.14	0.16	0.78	1.5
Kansas Wheat	1.12	0.13	0.87	1.5
Standard Deviation of Farm Yield to Standard Deviation of County Yield				
Illinois Corn	1.11	0.18	0.8	1.54
Illinois Soybeans	1.24	0.2	0.92	2.04
Kansas Soybeans	1.21	0.15	0.77	1.51
Kansas Wheat	1.23	0.17	0.81	1.7
Annual Ratio of Farm Revenue to County Revenue				
Illinois Corn	1.08	0.09	0.76	1.25
Illinois Soybeans	1.13	0.18	0.74	2.27
Kansas Soybeans	1.14	0.17	0.78	1.52
Kansas Wheat	1.12	0.14	0.85	1.52
Standard Deviation of Farm Revenue to Standard Deviation of County Revenue				
Illinois Corn	1.09	0.14	0.71	1.41
Illinois Soybeans	1.11	0.15	0.82	1.55
Kansas Soybeans	1.19	0.18	0.87	1.63
Kansas Wheat	1.18	0.21	0.73	1.88

	Mean	Standard Deviation	Minimum	Maximum
Size of County Squared Mile				
Illinois Corn	719	265	222	1184
Illinois Soybeans	714	277	314	1184
Kansas Soybeans	620	182	457	1428
Kansas Wheat	875	230	539	1428
Farm Planted Acre				
Illinois Corn	378	245	34	1172
Illinois Soybeans	390	235	33	852
Kansas Soybeans	398	253	118	1090
Kansas Wheat	502	275	70	1025

Source: Original calculations using data from Illinois Farm Business Farm Management (FBFM) program, Kansas Farm Management Association (KFMA), U.S. Department of Agriculture, National Agricultural Statistical Service, and National Association of Counties.

<Table 5> Pooled Regression Results for Share of Farm Yield Loss Systemic with County Yield and Revenue Loss for Losses Greater than 15% for Farm and County

Independent Variable	Yield		Revenue	
	(1)[A]	(2)[A]	(3)[A]	(4)[A]
Correlation (X)	0.96***	0.88***	0.63***	0.57***
	(0.24)	(0.21)	(0.12)	(0.12)
Illinois–Soybeans	-0.03	0.09	-0.39**	-0.34**
	(0.24)	(0.21)	(0.15)	(0.15)
Kansas–Soybeans	0.12	0.31	0.45	0.52*
	(0.43)	(0.37)	(0.31)	(0.31)
Kansas–Wheat	0.08	0.06	0.04	0.02
	(0.27)	(0.24)	(0.18)	(0.18)
X * Illinois–Soybeans	-0.12	-0.22	0.49***	0.44**
	(0.30)	(0.26)	(0.18)	(0.18)
X * Kansas–Soybeans	-0.21	-0.4	-0.35	-0.41
	(0.51)	(0.44)	(0.37)	(0.37)
X * Kansas–Wheat	-0.15	-0.07	0.04	0.06
	(0.34)	(0.29)	(0.23)	(0.23)
Average Farm to County Yield/Revenue Ratio		0.20**		0.01
		(0.10)		(0.08)
Farm to County Standard Deviation Ratio		-0.47***		-0.15**
		(0.06)		(0.07)
Farm Planted Acre		0.00		0.00
		0.00		0.00
County Size		0.00		0.00**
		0.00		0.00
Intercept	-0.17	0.21	-0.05	0.06
	(0.20)	(0.21)	(0.09)	(0.13)
Observations	185	185	185	185
R^2	0.371	0.541	0.440	0.477

Note: A. Standard Error of the coefficient is presented within the parenthesis. *, **, *** denotes statistical significance with 90%, 95%, and 99% statistical confidence, respectively.

Source: Original calculations using data from Illinois Farm Business Farm Management(FBFM) program, Kansas Farm Management Association (KFMA), U.S. Department of Agriculture, National Agricultural Statistical Service, and National Association of Counties.

No fixed effect or interaction variables were significant in either yield model. Thus, no variation was found across state-crop combinations in the power and magnitude of correlation to explain systemic yield loss. However, in both revenue models, the fixed effect and interaction variable for Illinois soybeans were significant with 95% statistical confidence. It is not clear why Illinois soybeans would be significant in the revenue model but not in the yield model.

5. Conclusions

5.1. Summary

This paper examined the power of the correlation between farm and county yield/revenue deviations to explain the share of farm loss that is systemic with the county. It used annual yield data for farms that participated in the Illinois Farm Business Farm Management and Kansas Farm Management Association in all or all but one year from 1973 through 2012. Expected yield was estimated using a 5 year Olympic moving average and a linear trend-line regression.

Correlation between farm-county yield/revenue deviations is found to be a statistically significant explanatory variable, but it explains less than 50% of the share of variation in farm loss systemic with county loss. Explanatory power increased to around 50% when other variables were added to the model, in particular the ratio of the farm's standard deviation to the county's standard deviation of yield/revenue variation from expected value.

5.2. Implications and Limitations

The findings of this study are consistent with the existing literature which argues that county variability may not be closely associated with farm variability. The findings of this study thus raise questions about the efficacy of area yield and revenue insurance products in helping farmers manage their risk. Such products have garnered considerable attention in recent years(eg., Hill, Robles, & Ceballos, 2016). Specifically, the basis risk, or the difference in the variability of yield and revenue on an individual farm vs. the county, is a significant cost to the effective risk management performance of area contracts. It is thus not surprising that the findings of this study are consistent with the lack of use of county yield products in the U.S. Most U.S. farmers have the choice of county or individual farm insurance products. However, 98% of acres insured in the U.S. are insured with products that indemnify based on a farm's yields(U.S. Department of Agriculture, Risk Management Agency, November, 2016).

An implication of the study is that policy makers and marketing managers of agricultural commodities need to consider the relationship between farm and county losses when designing policies for agricultural marketing or when making marketing decisions, as the performance of the marketing strategy implemented by a farm in a county is closely associated with the performance of another farm of the same county as well as the performance of a farm of another county.

A limitation of this study is that we have focused only two U.S. States, Illinois and Kansas, and three agricultural commodities, corn, soybeans and wheat. Therefore, generalization of the results into other U.S. States or other crops should be careful, though it is highly expected that the relationship between farm and county losses could be very similar for other U.S. States and agricultural commodities, and even for other countries that are similar to the United States in terms of the size and the structure of agriculture.

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