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How Crop Insurance affects Farm Business Survivability

Youngjune Kim

PhD student

Department of Agricultural Economics

Kansas State University

yjkim@ksu.edu

Dustin L. Pendell

Associate Professor

Department of Agricultural Economics

Kansas State University

dpendell@ksu.edu

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1. Introduction

Farmers are often faced with innate risks in terms of production and price. Risks stem from unexpected changes in price and quantity brought about by exogenous factors such as adverse weather, crop pest or diseases, and unpredictable changes in demand. In many countries, crop insurance was designed to assist farmers in coping with such risks. Most crop insurance research focuses on optimal contract design, moral hazard, and adverse selection to make a crop insurance program more attractive. However, there have been relatively few studies that examine how crop insurance affects the farm business.

Crop insurance payments have played an important role and grown in size across time. Crop insurance coverage is in the form of revenue insurance which not only guarantees a certain portion of expected revenue, but also reimburses yield losses (Goodwin, 2015). Indeed, crop insurance subsidies have been significantly increased and now protects over 298 million acres of farmland with liabilities in excess of $102 billion, since the U.S. federal crop insurance program was initially established on a small scale in 1938 (Risk Management Agency, 2015). The average size of the payment for the Kansas Farm Management Association (KFMA) farms dramatically increased from $21,186 to $40,363 per operation between 2002 and 2014. Hence, it is important for policy makers to identify to what extent crop insurance affects farm survival. Additionally, determining which characteristics besides crop insurance influence farm survivability.

The main objective of this study is to identify if, and to what degree, crop insurance payments have influenced farm business survival. In addition to crop insurance payments, this study will also examine how farm characteristics affect the probability of farm survivability.

2. Previous Literature

There have been a few studies that have explored the factors could impact farm exit. These factors include subsidy decoupling (Kazukauskas et al, 2013), commodity payments (Ahearn, Yee, and Korb, 2005), price strategy (Foltz, 2003), government payments (Key and Roberts, 2006) and farm characteristics (Kimhi and Bollman, 1999; Weiss, 1999; Glauben, Tietje, and Weiss, 2006; Breustedt and Glauben, 2007). However, little is known about the impact of crop insurance on survival of individual farms.

This study employed survival analysis to analyze farm business survivability. Survival analysis is a method used for analyzing data where the outcome variable is the survival time, or duration of time, until an event of interest happens. This framework has been widely used in the medical research field, but rarely utilized in farm level research. One such study that applied survival analysis at the farm level is Key and Roberts (2006) where they examined the effect of government payments on farm survival. Because they used Ag. Census data, the authors were limited to the amount of analysis they could conduct at the farm level. For example, the Ag. Census is only conducted every five years and does not record various financial data. To date, this research is unique as it is the first article to assess the effect of crop insurance on farm business survivability using survival analysis.

3. Methods

The Cox proportional hazard model is used to determine the effects of crop insurance and other factors on the probability of farm failure (Cox, 1972). The conditional probability of failure for the farm right after time t which survived until time t is called a hazard function:

(1) $$h(t;X) = h_0(t)\exp(\beta' X)$$

where β is an unknown vector, X is a vector of explanatory variables, and $h_0(t)$ is the baseline hazard function. The Cox proportional hazard model is a semi-parametric model consisting of both nonparametric parts $h_0(t)$ and parametric parts $\exp(\beta' X)$. This nonparametric characteristic makes it possible to derive exact estimates without specifying a functional form.

This study employs partial likelihood proposed by Cox (1972) to obtain the estimates. Partial likelihood can be formulated as the product of the conditional probabilities for every observed event:

(2) $$L(\beta) = \prod_{i=1}^{D} \frac{exp(X_i)}{\sum_{j \in R(t_i)} exp(\beta' X_j)}$$

where $R(t)$ is the risk set at time t_i indicating the cases are at risk of experiencing failure at time t_i, and D is the number of failed cases. By finding a value of β that maximizes the log-likelihood function of (2), we obtain the estimates β.

4. Data

The data used in this study are from the KFMA and consists of a 2007-2014 panel of farms. This study sets 2007 as the beginning year of analysis. The amount of crop insurance payment for the KFMA farms rapidly increased in 2007 by 134% from the previous year due to severe weather. Thus, we attempt to analyze the impact of crop insurance payment in 2007 on the farm survival. In addition, farm characteristic variables were used to examine the relationship between farm characteristics and farm survival: crop income (log scale), indicators for five crop categories, indicators for seven operator’s age categories, indicators for business organization type (partnership or sole proprietor), crop labor percentage and debt-asset ratio. The mean and standard deviation of the survival year and the explanatory variables are presented in table 1.

To capture the impact, this study estimates a Cox proportional hazard function for 1029 farms operating in 2007 by following up their subsequent survival every year. Since this study attempts to show how crop insurance affects farm survivability, the empirical analysis is applied to farms that received a crop insurance payment.

To consider sample heterogeneity, we classify farms into five crop categories, corn, grain sorghum, wheat, soybeans and other crops, which are the main crops in Kansas. If any of these crops account for at least 50% of crop income[1], they are assigned as corn, grain sorghum, wheat and soybean, respectively. If none of these crops takes up more than 50% of crop income, they are classified as "other crops". The survival rates by farm category are represented in table 2. In general, about 50% of crop farms in 2007 were shown to remain in business in 2014. Wheat farms were likely to survive longest, followed by soybeans, corn and grain sorghum.

There is no specific variable indicating when a farm has gone out of business in the KFMA. Hence, we define a surviving year as how long the farm has been operating before the farm no longer appeared in the KFMA. In addition, a farm is assumed to be out of business if there is no response. This study do not consider a farm to have a different operator.

Farms that began operating prior to the initial year cannot be observed (left

[1] Crop income is defined as the sum of grain income and cash crop income.

truncation)[2]. We do not observe business until 2007, the beginning year of analysis, even though the event of interest, farm survival, has already occurred prior to 2007. For example, an observation is left truncated at seven years if farm initiated business in 2000. In addition to left truncation, observation is terminated before all farms' survival are realized (right censoring). We can no longer follow up farms which still survive in 2014, while farm failure has not happened at the end of observation, 2014. Both left truncation and right censoring problems are taken into consideration with the Cox proportional hazard model.

5. Results

Table 3 represents cox proportional hazard model estimates for three different specifications. In all specifications, five farm characteristic variables were used: crop income (log scale), indicators for five crop categories, indicators for seven operator's age categories, indicators for business organization type and crop labor percentage. We interact the natural logarithm of crop insurance payment with the indicators for crop income quartiles to analyze how different the effects of crop insurance payment on farm survival are for each quartiles. Crop insurance payments is measured in natural logarithm to facilitate interpretation of the coefficients.

In the specification (2), a measure of debt-asset ratio was introduced. In the specification (3), in addition to the debt-asset ratio, we also introduce the initiation year fixed effects indicating when a farm initiated their business to control for policy change on crop insurance across time.

Across all specifications, crop income is negatively associated with farm failure.

[2] KFMA data was first observed in 1973. For farms that started their business prior to 1973, we assume they began operating in 1973.

These effects were statistically significant at the 1% significant level. Since crop income is measured in log scale, these coefficients indicates that the rate of farm failure decreases by about 2.7~3.0% as crop income increases by 10%. It is quite clear that farms with higher crop income are likely to survive longer.

An increase in crop labor percentage is positively correlated with hazard rates. Crop labor percentage is an index indicating the degree of specialization. Thus, we find that farms that are more diversified are more likely to survive. Additionally, debt-to-asset ratio is statistically significant variable associated with hazard rate at the 10% significant level. The positive coefficients in (2) and (3) indicate that farms with higher debt-to-asset ratio are likely to fail.

Up to 50-60 years old producers, the rate of farm failure decreases as farmers are getting older. This result is because older farms are more experienced and tends to keep remain in farming compared to younger farms. However, the hazard rate increases gradually after the age of 60-70. This is because they will sell or close the business as they reach retirement. Additionally, hazard rates are lower on farms with sole proprietor rather than partnership-owned.

In all specifications, the logarithm of crop insurance payment interacted with crop income quartiles are statistically significant variable for all crop income quartiles, except for highest crop income farms. Since crop insurance payments is measured in log scale, the coefficients can be interpreted as an elasticity. That is, the coefficients indicates that what degree the probability of farm business failure change to a change in crop insurance payments. For the second quartile, third quartile and top-quartile of crop income farms, an increase in crop insurance payments reduce the rate of farm failure. For example, in the 3rd model, as crop insurance payment increases by 10%, the probability of farm failure decreases by 2.9%, 2.0% and 1.0% for the second quartile, third quartile and top-quartile of crop income farms, separately. We find that crop insurance payment have played an important role in farmer's coping with risks. Meanwhile, an increase in crop insurance payments is positively associated with the rate of farm failure for bottom-quartile of crop income farm. This effect is statistically significant at the 1% level. This result implies that small farms are more likely to quit farming and finding other job instead of remaining in business after natural disasters occurred or economic crisis came about.

6. Conclusions

Crop insurance payment increases farm survivability across all farms except lower crop income farms. By making farm more profitable, crop insurance payment helps them coping with various risks. On the other hand, for bottom-quartile of crop income farm, crop insurance have statistically significant negative effect on farm survival. We also find that crop income and operator's age (up to 60-70 years old) reduce the rate of farm failure and older farm (over 70), specialization on crop and debt-asset ratio are negatively associated with farm survivability.

One of the limitations of this study is that a farm is out of business if they do not renew their membership in the KFMA. Although we do not know if a farm actually exited the business, the farm is assumed to be failed. In this case, the results could be biased. Thus, it would be an important area to predicting missing observations using the observed data for future research.

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Table 1. Summary Statistics

Variable	Unit	Mean	Std. Dev
Survival year	Years	5.3	2.4
Crop insurance payment	$	42,532	62,728
Crop income	$	327,105	353,382
Operator's age	Years	55.4	11.7
Crop labor percentage	%	0.83	0.20
Debt asset ratio	%	0.35	0.30

Table 2. The Survival Rates by Farm Category

Farm Category	2007	2014
All crop farms	1029	581 (53.9)
Corn	178	96 (51.3)
Grain Sorghum	39	20 (49.5)
Wheat	95	47 (57.5)
Soybeans	127	79 (56.5)
Other crops	590	339 (57.5)

Notes: The survival rate (in parentheses) is a percentage of the number of farms survived in 2014 out of the number of farms in 2007.

Table 3. Cox Proportional Hazard Model Estimates under different specifications

	(1)		(2)		(3)	
Variable	Coeff.	SE	Coeff.	SE	Coeff.	SE
Log Crop income	-0.281***	0.107	-0.277***	0.107	-0.300***	0.107
Corn	0.250*	0.142	0.236*	0.142	0.182	0.143
Grain Sorghum	0.141	0.246	0.141	0.246	0.076	0.253
Wheat	0.405**	0.167	0.407**	0.167	0.450***	0.169
Soybeans	-0.009*	0.168	-0.003	0.168	0.000	0.172
Operator's age 30-40	-0.086	0.339	-0.053	0.340	-0.121	0.345
Operator's age 40-50	-0.232	0.324	-0.210	0.324	-0.310	0.332
Operator's age 50-60	-0.364	0.321	-0.326	0.322	-0.375	0.329
Operator's age 60-70	-0.036	0.325	0.012	0.326	-0.028	0.333
Operator's age 70-80	0.334	0.343	0.425	0.348	0.453	0.355
Operator's age 80-90	0.780**	0.397	0.910**	0.405	0.936**	0.413
Organiz. = Partnership	0.085	0.232	0.062	0.232	0.006	0.238
Organiz. = Sole proprietor	-0.022	0.172	-0.025	0.172	-0.093	0.176
Log Crop labor percentage	0.229	0.158	0.217	0.157	0.233	0.159
Debt asset ratio	-		0.293*	0.168	0.327*	0.177
Initiation year	-		-		Yes	
Crop income quartile	Yes		Yes		Yes	
Log Crop. Pay * Crop income Q1	0.250***	0.079	0.249***	0.080	0.272***	0.083
Log Crop. Pay * Crop income Q2	-0.253**	0.107	-0.263**	0.107	-0.296***	0.111
Log Crop. Pay * Crop income Q3	-0.161*	0.099	-0.167*	0.099	-0.201**	0.103
Log Crop. Pay * Crop income Q4	-0.095	0.098	-0.095	0.098	-0.101	0.101

Notes: Single, double, and triple asterisk (*) denote coefficient is significant at the 10%, 5%, and 1% level, respectively. "Yes" indicates variables were included in the regression.