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Disaster Assistance and Crop Insurance Participation in US

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Abstract

This research examined factors influencing farmer purchase of crop insurance and receipt of disaster assistance payments using survey data for more than 13,000 farms across 27 U.S. states. Using a bivariate probit model some main findings are as follows. The probability of participating in federal crop insurance programs is (a) lower for farmers more than 65 years of age; (b) increasing with farmer education and farm sales; (c) lower for farms where farm income is a small share of household income; and (d) higher in states with higher average temperatures and lower average precipitation. The probability of receiving disaster payments (a) increases as farms depend more on farm income for their total household income; (b)increases with sales in peanut farming and cattle ranching; (c) greater in states experiencing drier or wetter than normal hydrologic conditions; and (d) greater in states experiencing warmer than normal temperatures. In addition, previous research using state-level data found agricultural disaster payments were higher in states with congressional representation on subcommittees overseeing USDA's direct disaster payment program. The farm-level analysis of this thesis supports this earlier finding. Farmers in states with such representation had higher probabilities of receiving disaster payments, controlling for other factors.

CHAPTER ONE

Introduction

This study examines the various economic factors that influence farmer demand for crop insurance and receipt of disaster payments Explanatory factors in this study include (a) farmer and operation characteristics, (b) climate and climate variability, and (c) political variables influencing distribution of disaster payments.

Farming is an inherently risky and uncertain activity, with farm returns vulnerable to seasonal climate variability and extreme weather events such as droughts, floods, hail etc. Federal crop insurance programs and congressionally mandated ad-hoc disaster payments are the two main policies used by the federal government to mitigate financial losses of farmers. Generally private insurance companies are involved in the marketing and selling of crop insurance policies. Farmers should select the insurable crop, coverage level (yield or price coverage) and pay the premium decided by federal government. The federal government generally subsidizes a portion of the premium.

Background

The Federal Crop Insurance Corporation (FCIC) is a government corporation that is managed by the Risk Management Agency (RMA) of the United States Department of Agriculture (USDA). The FCIC was first designed in 1938 in response to economic hardships brought on by the Great Depression and Dust Bowl. FCIC indemnifies farmers if the yield falls below the expected level caused by various factors such as pests, diseases and weather disasters (flood, drought, hail etc.). These efforts were not successful due to low participation from farmers. The program suffered from lack of reserves to pay claims. Because of limited participation in crop insurance programs, Congress tried to assist the farmers with direct payments and disaster assistance. To increase the participation in FCIC, Congress passed the Federal Crop Insurance Act of 1980, intended to encourage a partnership between U.S government and private insurance companies to provide farm insurance. However, participation rates remained low. Some analysists have argued that the disbursement of ad hoc disaster assistance and emergency loans undermined the crop insurance participation (Goodwin and Rejesus, 2008; Barnett, Skees, and Hourigan, 1990).

The Federal Crop Insurance Reform Act of 1994 made it mandatory for farmers to purchase crop insurance program to be eligible for disaster payments. Catastrophic coverage (CAT) was designed to promote compulsory participation. This coverage allows the farmers to counter their losses higher than 50% of average yield. The government subsidized the premiums under CAT coverage. This act was repealed in 1996 as requiring purchase of crop insurance proved unpopular with the producers.

However farmers receiving disaster payments were still required to purchase crop insurance.

In 1996, the USDA Risk Management Agency (RMA) was created to administer FCIC programs and other risk management and education programs to support U.S. agriculture. Participation in federal crop insurance programs increased dramatically because the new programs included significant insurance premium subsidies. In 2000, Congress passed the Agriculture Risk Protection Act (ARPA), which further increased crop insurance subsidy levels. In 2004 more than 220 million acres were insured through the program, protecting around $4 billion of crop value.

Farmers have a variety of choices of crop insurance, including revenue coverage, yield coverage, and CAT coverage on a county-by-county basis for number of crops. The choice of appropriate coverage has become a complex decision as the options to purchase crop insurance have increased.

The direct disaster payment program was instituted under the Agricultural and Consumer Protection Act of 1973. Under this program the government pays direct cash to the farmers who suffer catastrophic losses. Disaster payments are ad hoc. Legislators often usually decide whether or not to provide direct payments to farmers after a disaster occurs.

CHAPTER TWO

Literature Review

There have been many studies that attempt to estimate the models of crop insurance purchase decisions and disaster payment receipts of producers. Knight and Coble (1997) studied on Multiple Peril Crop Insurance (MPCI) issues and participation in depth, surveying literature from 1980 to 1997. They mainly focused their study on the effect of moral hazard on adverse selection on the actuarial performance of MPCI program.

Goodwin and Rejesus (2008) estimated a joint model with three equations evaluating interrelationships between crop insurance purchase decisions, disaster relief receipts and farm profitability. The study also focused on the factors influencing crop insurance demand. They found that higher premium rate has negative effect on demand for crop insurance while loss ratio and diversification has a positive effect on demand for crop insurance. The important finding of the study is the inverse relationship between disaster assistance and crop insurance.

Black and Dorfman (2000) used a logit model to model the probability of purchasing crop insurance by cotton and peanut farmers in Georgia. Southern U.S farm-level data was used for the study. Data was from a mail survey conducted by University of Georgia's Center for Agribusiness and Economic Development. Their study revealed that main reason for the low participation in crop insurance was growers' abilities to self-insure by diversification. Growing multiple, diverse crops substituted for insurance purchase. They found that age, education and income had a negative effect on crop insurance purchase, while farm debt and size had a positive effect on demand for crop insurance.

Smith and Goodwin (1996) analyzed the relationship between agricultural chemical use and the crop insurance purchase decision. Their study included sample of 1136 dry land wheat farmers from Kansas in 1992. A simultaneous model was employed because crop insurance purchase and input usage decisions were potentially joint decisions supported by the Wu-Hausman test. Their study found an inverse relationship between the purchase of crop insurance and chemical usage.

Goodwin (1993) conducted estimated the demand for crop insurance using county-level panel data from Iowa Corn producers from 1985 to 1990. He found the demand for crop insurance was more elastic in counties with low loss-risks than counties where producers receive higher indemnities compared to their premium payments. The study also revealed that value of land, percentage of county acreage in rental, and farm size increased the demand for crop insurance. The interaction variable of premium with loss ratio has a positive coefficient on crop insurance and was highly significant.

Garrett, Marsh, and Marshall (2006) explored the effect of political influence on agricultural disaster relief in 1990s. They also studied the impact of non-political factors such as weather and farm size on direct disaster payments. Their study included data from 48 U.S states through 8 years from 1992 through 1999. Their dependent variable was the amount of agricultural disaster payments received by a state in a given year. They used the tobit regression model to study the effect of explanatory variables on disaster payments as the dependent variable is censored (with some states receiving no payments in some years). They found that intense precipitation causes increased receipt of disaster payments. Another important finding of the study was that states with representation on the House Appropriation Subcommittee received higher disaster payments. Increase in the number of farms has a significant and positive effect on disaster payments. The West North Central regions of the country also received more disaster payments, compared to other regions.

Barry et al. (2002) analyzed the preferences of producers and product attributes with respect to crop insurance participation. Data was collected from a mail survey of 868 producers in Illinois, Iowa and Indiana. The study found that farmer age, farm acreage, debt to asset ratio, and risk management tools like hedges/options had a significant positive effect on demand for crop insurance. They also found that producers who had higher debt to asset ratios, larger farms, and more education preferred revenue insurance to yield insurance.

Changnon (2002) studied the effects of drought forecasts on crop insurance decisions in Midwestern states of Illinois, Indiana, Iowa, Nebraska and Ohio. In March of 2000, the United States Departments of Commerce, Agriculture and Interior issued a joint drought forecast, based on observations by the National Oceanic and Atmospheric Administration (NOAA). Changnon surveyed 1,448 producers, which allowed a quantitative assessment and their reactions to the drought forecast. Of the 1,017 respondents in the five states 39% indicated that they had adjusted production practices and 40% indicated that they made changes to their crop insurance coverage based upon the drought forecast.

CHAPTER THREE

Description of Data and Regression Variables

Description of Data:

The data for the study is collected from various sources. Data on the personal characteristics of producers is obtained from the National Agricultural, Food and Public Policy Preference Survey. The survey was conducted between October 2005 and April 2006. This is cross sectional data collected individually from the farmer's response to a mail questionnaire. The survey includes data from 27 participating U.S. states. There is information on the type of crops grown such as food grains, soybeans, cotton, dry beans, tobacco, horticultural crops, forages and dairy grown by the farmers. In all, 15,603 farmers responded to the questionnaire from the 27 states. After data cleaning i.e. removal of missing values, 13603 observations were taken into consideration for the study. Farmers were asked whether they participated or received any benefits from crop insurance in the recent years. They were also asked whether they had received any disaster assistance in the recent years. Weather data on temperature, precipitation and palmers hydrological drought index was gathered from the National Oceanic Atmospheric Administration's National climatic data center. The data on each state's crop insurance premium rate was collected from USDA's Risk Management Agency. Data on political variables was collected from 109th Congress with four subcommittee's membership that oversees direct disaster relief through various Government websites.

Description of Variables used in the Model:

Dependent Variables:

Crop Insurance:

Crop insurance is a binary variable and takes the value of one if farmer participated in crop insurance programs in recent years and value of zero, otherwise. About 25% of respondents reported that they did participate in a crop insurance program in the recent years.

Disaster Assistance:

Disaster Assistance is also a binary variable and takes the value of one if the farmer received direct disaster payments in recent years and value of zero, otherwise. About 30% of farmers reported receiving disaster payments in recent years.

Explanatory Variables:

Age:

Farmer age was recorded as a categorical variable.

Table 3.1: Classification of Age

Category	**Age group of farmers**
Agele25	Under 25 years
Age25_34	25-34 years
Age35_44	35-44 years
Age45_54	45-54 years
Age55_64	Above 65 years

This variable is expected to have a positive sign on crop insurance participation. As the age of farmer increases, he will be more experienced and buy crop insurance as a risk management tool.

Education:

Education is an ordered categorical variable in an ascending order from category 1 to 6.

Table 3.2: Classification of Education

Category	**Education level completed**
Edu_1	Grade School
Edu_2	Some High School
Edu_3	High School
Edu_4	Some College
Edu_5	College Bachelor's Degree
Edu_6	College Advanced Degree

This variable is expected to have a positive sign on purchase of crop insurance. Educated farmers appear to be better managers and are supposed to be aware of better risk management tools and likely to purchase crop insurance.

Sales Class:

Sales class is the average annual market value of agricultural products sold from farmer's farm or ranch. This income does not include government payments. Sales class is classified into seven categories:

Table 3.3: Classification of Sales Class	
Category	**Sale Class of farmers**
Saleclass_1	Under $10,000
Saleclass_2	$10,000 - $49,999
Saleclass_3	$50,000 - $99,999
Saleclass_4	$100,000 to $249,999
Saleclass_5	$250,000 to $499,999
Saleclass_6	$500,000 to $999,999
Saleclass_7	$1,000,000 or greater

Income from Farming: (Income from farm/Total Income)

This variable tells about the percentage of family income derived from total farming. This is classified into five categories:

Table 3.4: Classification of Farm Income as a Share of Total Household Income	
Category	**Farm Income Share**
FarmY/TotalY_1	None
FarmY/TotalY_2	1-25%
FarmY/TotalY_3	26-50%
FarmY/TotalY_4	51-75%
FarmY/TotalY_5	76-100%

This variables measures diversification of household income across agricultural and non-agricultural activities. Households with a lower share of income from farming face relatively less risk to household income from farming risk.

% Own Farm:

This variable tells about the percentage of land a farmer owns, divided into five categories. :

Table 3.5: Classification of %Own Farm	
Category	**Percentage of farm land that is owned**
%Ownfarm_1	None
%Ownfarm _2	1-25%
%Ownfarm _3	26-50%
%Ownfarm _4	51-75%
%Ownfarm _5	76-100%

The categorical data was used to construct binary dummy variables indicating whether a farmer belonged (or did not) belong in each category.

Crops and Livestock:

Variables were included that measured the share of different crop and livestock categories in to total farm sales. Total share values summed to one.

The following are the crops included in the questionnaire:

Food grains, soybeans, cotton, pulses, peanuts, sugar, tobacco, special crops, forages, other crops, aquaculture, cattle, dairy, hogs, sheep and poultry.

Political Variables:

Political variables were included in the model to see the effect of political influence on disaster payments. The four subcommittees that oversee the disaster relief payments were included in the model. Two subcommittees are from the House of Representatives and two are from the Senate. The two House subcommittees that oversee the disaster relief are:

1) House Subcommittee on General Farm Commodities and Risk Management.
2) House Appropriation Subcommittee on Agriculture, Rural Development, Food and Drug Administration, and Related Agencies.

The two Senate subcommittees that oversee the disaster relief are:

1) Senate Subcommittee on Research, Nutrition, and General Legislation
2) Senate Appropriation Subcommittee on Agriculture, Rural Development.

All the members are from 109th Congress. Four dummy variables are created for the four subcommittees. Each subcommittee is a dummy variable and takes the value of 1 if the legislator of the state is in a disaster committee and 0 otherwise. Garrett, Marsh, and Marshall (2006) found that these political influence variables were important determinants of state-level receipt of agricultural disaster relief in 1990s.

Crop Insurance Premium:

This variable is calculated as:

(State Crop Premium- Total Subsidy received by state) / Net Acres of state.

Crop Insurance Premium is expected to have a negative sign on crop insurance purchase.

Weather Variables:

Precipitation, Temperature and Palmers Hydrological data is included in the study to study the effect of weather variables on crop insurance purchase and disaster payments.

Long run Precipitation:

30-year annual average data on precipitation is collected for each state.

Long run Temperature:

The 30-year annual average temperature for each state.

Palmer's Hydrological Drought Index (PHDI):

This variable captures the monthly moisture conditions that depart from the normal. The annual average data for 2005 is collected for each state. Based on this data two variables are created to capture the absolute drought and flood for each state.

Drought:

Drought variable captures negative deviation from normal. Drought of each state represents minimum {PHDI, 0}.Zero is the maximum value for this variable and minimum is the negative value.

Flood:

Flood variable captures positive deviation from normal. Flood of each state represents maximum {PHDI, 0}. This variable has a maximum positive value and minimum is zero.

CHAPTER FOUR

Nonparametric Measures of Association for Contingency Tables:

Non-parametric tests of association are used to test the hypotheses of relationship between two variables such as sales class and purchase of crop insurance. This test not only measures the strength of association between two variables but also the statistical significance between them. The relationship between sale class and purchase of crop insurance can be arranged as 6 × 2 contingency tables. Sales class with six rows is arranged in increasing order from sale class1 to sale class6. Farmers participating in crop insurance are arranged in two columns with "yes" response and "no" response. Chi-square test of independence is the most common method of significance testing for data cast in a contingency table.

Sale Class is divided in to six classes as follows:

- Under $10,000 - Sales Class1
- $10,000 - $49,999 - Sales Class 2
- $50,000 - $99,999 - Sales Class 3
- $100,000 - $249,999 - Sales Class 4
- $250,000 - $499,999 - Sales Class 5
- $500,000 - $999,999 - Sales Class 6
- $1,000,000 and over - Sales Class7

Ho: There is independence between two variables in a contingency table.

Ha: The variables are not independent.

Problems with Chi-square Test:

The above test does not tell us anything about particular type (positive or negative) of association between the two variables.

The above test statistic is assumed to be distributed as chi-square irrespective of sample size. The sampling distribution of the chi-square test statistic is not known. The chi-squared test does not allow having one-sided alternative stating that association exists in a particular direction. If the sample size is large, the above test always leads to rejection of null hypothesis as the value of test statistic is highly inflated by small expected frequencies. Results of farmers participating in Crop insurance program for all 27 states are shown in Table 4.1.

Table 4.1: Relationship between Sale Class and Crop Insurance Participation

	Farmers participating in crop insurance program		
Sales Class	No	Yes	Percent responding Yes
Sales Class 1	2800	84	2.9
Sales Class 2	2230	416	15.7
Sales Class 3	1456	595	29
Sales Class 4	1969	1232	38.5
Sales Class 5	866	658	43.2
Sales Class 6	446	329	42.5
Sales Class 7	360	165	31.4

The above table shows that the relationship between sale class and purchase of insurance is not clear. The farmers in higher sale class participate more in crop insurance compared with lower Sale Class farmers, but the farmers with highest degree (sale class7) has lower influence in purchasing crop insurance compared to Sale Class5.

The association between Sales Class and different yes-no responses of crop insurance purchase by producers need to be measured. The most common method used to measure the association is Pearson correlation coefficient, which assumes that two variables are measured numerically and have a bivariate normal distribution.

Sale Class and yes/no variables in the above table are categorical / ordinal. Sales Class move from Sales Class 1 (under $10,000) to Sales Class 6 ($1,000,000 and over). The yes/no responses can be considered as binary response variable with 1 for yes and 0 otherwise. “Yes” category is given more weight than “No” category. We can expect the farmers to purchase insurance if the expected utility is positive and not to purchase crop insurance if expected utility is negative.

The Goodman-Kruskal Gamma (γ)

An alternative non-parametric measure of association for ordered contingency table is the Goodman-Kruskal gamma coefficient. The value of this gamma coefficient lies between -1 and 1, where -1 is for negative association and 1 is for positive association. Gamma is defined as surplus of concordant pairs over non-concordant (discordant) pairs, as a percentage of all pairs. Tied pairs are ignored.

$$\boldsymbol{\gamma = (C-D) / (C+D)}$$

$\gamma = 0$ under complete independence. There will be more concordant pairs than non-concordant pairs for a positive γ, which represents positive association. Similarly there will be more discordant pairs than concordant pairs for a negative γ, which represents a negative association.

Let us look at the example of association between sales class and purchase of crop insurance. Recall table 4.1.

	Purchase Crop Insurance	
Sales Class	**No**	**Yes**
Sales Class 1	2800	84
Sales Class 2	2230	416
Sales Class 3	1456	595
Sales Class 4	1969	1232
Sales Class 5	866	658
Sales Class 6	446	329
Sales Class 7	360	165

The above table is arranged in X*Y form, where X is the number of rows and Y is the number of columns. Calculation of concordant pairs for the above 7*2 contingency table is as follows:

Concordant pairs are the ones with the pairs between cells from right to down from other.

Pick a cell from 1st row and 1st column. A concordant pair with 2800 is calculated as 2800 * (416 + 595 + 1232 + 658 + 329 + 165) = 9506000. Similarly concordant pair with 2230 is calculated as 2230 * (595 + 1232 + 658 + 329 + 165) = 6643170. Repeat the same for 1456. The concordant pairs are 1456 * (1232 + 658 + 329 + 165) = 3471104. Concordant pair for 1969 are 1969 * (658 + 329 + 165) = 2268288. Concordant pairs for 866 are 866 * (329 + 165) = 427804 and the concordant pairs for 446 are 446 * 165 = 73590 All the above concordant pairs sum up to 9506000 + 6643170 + 3471104 + 2268288 + 427804 + 73590 = 22,389,956.

Discordant pairs are the ones in the cell from left to down from the other. Discordant pairs for the above table as follows:

84 * (2230 + 1456 + 1969 + 866 + 446 + 360) = 615,468

416 * (1456 + 1969 + 866 + 446 + 360) = 2,120,352

595 * (1969 + 866 + 446 + 360) = 2,166,395

1232 * (866 + 446 + 360) = 2,059,904

658 * (446 +360) = 530,348

329 * 360 = 118,440

Sum of above discordant pairs = 615468 + 2120352 + 2166395 + 2059904 + 530348 + 118440 = 7,610,907

γ = (C-D) / (C+D)

γ = (22,389,956 – 7,610,907) / (22,389,956 – 7,610,907)

γ = 0.4926

The gamma of 0.4926 represents a positive association between sales class and purchase of crop insurance. The above tests the strength of association of the cross-tabulated data. The gamma value gives us the proportionate reduction in error interpretation. Ignoring the tied pairs and guessing the ranking of two pairs based on knowledge of independent variable x and if we have y values for two randomly selected pairs, we will predict that if second x is more than the first, then the rank of second y value will be greater than rank of the first y value. So for the gamma of 0.4926, making predictions based on the above logic reduces the errors in predicting the rank of the columns by 49.26% compared to ignoring information about their association.

Relationship between Age and Crop Insurance Purchase:

Table 4.2: Relationship between Age and Crop Insurance

	Purchase Crop Insurance		
AGE	No	Yes	Percent responding yes
Age less than 25	24	7	22.6
Age between 25 – 34	315	147	31.8
Age between 35 – 44	1208	500	29.3
Age between 45 – 54	2913	1214	29.4
Age between 55 – 64	2940	1002	25.4
Age greater than 65	2724	609	18.27

$\gamma = (C-D) / (C+D)$

γ = (11026606 - 15403139) / (11026606 + 15403139)

γ = - 0.1655

There is a negative association between age and crop insurance purchase. The above gamma value tells us that based on the information about rows, errors can be reduced in predicting rank of columns by 16.55%.

Relationship between Farm Income / Total Income and Crop Insurance

Table 4.3: Relationship between Farm Income / Total Income and Crop Insurance			
	Purchase Crop Insurance		
Farm Income / Total Income	No	Yes	Percent responding yes
None	580	45	7.2
1 - 25%	3466	339	8.9
26 – 50%	1354	505	27.2
51 -75%	1171	644	35.5
76 – 100%	3553	1946	35.4

γ = (C-D) / (C+D)

γ = (18504616 - 7163674) / (18504616 + 7163674)

γ = 0.4418

There is a positive association between farm income as a share of total income and crop insurance purchase. The above gamma value tells us that based on the information about rows; errors can be reduced in predicting rank of columns by 44.18%.

Relationship between Percentage of Own Farm and Crop Insurance:

Table 4.4: Relationship between Percentage of Own Farm and Crop Insurance:

	Purchase Crop Insurance		
% Own Farm	No	Yes	Percent responding yes
None	614	223	26.6
1 - 25%	1034	715	40.8
26 – 50%	1065	749	41.3
51 -75%	1087	636	36.9
76 – 100%	6324	1156	15.5

$\gamma = (C-D) / (C+D)$

$\gamma = (7791630 - 17753973) / (7791630 + 17753973)$

$\gamma = -0.3899$

There is a negative association between percentage own farm and crop insurance purchase. The above gamma value tells us that based on the information about rows; errors can be reduced in predicting rank of columns by 38.99%.

Table 4.5: Relationship between Crop Insurance Participation and Disaster Assistance:

	Insurance no	Insurance yes
Disaster no	8082	1490
Disaster yes	2042	1989

Chi-square Test:

Chi-square test statistic between crop insurance and disaster assistance is 1700 with p-value <0.0001, which tells us there is an association between these two variables.

Gamma Test:

$$\gamma = (C-D) / (C+D)$$

$$\gamma = 13032518 / 19117678$$

$$\gamma = 0.68$$

Gamma value for above table is 0.68. This result tells us there is a strong positive relationship between crop insurance purchase and disaster assistance. Farmers who participate in crop insurance are more likely to receive disaster assistance, which is consistent with the study of Glauber (2007).

Relationship between Diversification and Farm Income / Total Income:

Table 4.6: Relationship between Diversification and Farm Income / Total Income

	Farm Y / Total Y _ 1	Farm Y / Total Y_ 2	Farm Y / Total Y_ 3	Farm Y / Total Y_ 4	Farm Y / Total Y_ 5
Diversification < .25	1	13	16	16	33
.25 ≤ Diversification <.5	86	582	347	390	1206
. 5 ≤ Diversification <.75	150	1117	593	593	1717
. 75 ≥ Diversification	388	2093	903	816	2543

Gamma Test:

$$\gamma = (C-D) / (C+D)$$

$$\gamma = - 4983095 / 41516739$$

$$\gamma = -0.12$$

Gamma value for above table is -0.12. The columns measure specialization with respect to agriculture and non-agriculture. The results seem to suggest that as farmers specialize more in crops they are less likely to focus just on farming.

CHAPTER FIVE

Econometric Model:

This study tries to explain farmer participation in federal crop insurance programs and receipt of agricultural disaster assistance as functions of explanatory variables such as those identified by various previous studies.

One dependent variable, crop insurance, takes the value of 1 if farmers participated in crop insurance programs and 0 otherwise. Similarly, another dependent variable takes the value of 1 if a famer received disaster payments and 0 otherwise. Probit model were used to study the economic factors influencing the crop insurance purchase and disaster payment outcomes.

$P(Y = 1 \mid X) = \Phi(X`\beta)$

Where P represents the probability

Φ represents the cdf of normal distribution.

The probit if considered as latent variable model can be written as:

$Y_i^* = \beta_i`X_i + \varepsilon_i$

Where β is a coefficient vector, X is a matrix of independent covariates and ε is an error term.

$Y_i = 1$ if $Y_i^* > 0$

$Y_i = 0$ if $Y_i^* \leq 0$

Where Y_i ~ N (0, 1) for probit model and i = 1 for crop insurance and i = 2 for disaster payments. The above model is estimated using maximum likelihood estimation procedure in STATA.

Seemingly Unrelated Bivariate Probit Model:

Y_1 and Y_2 are the discrete dependent variables representing a farmer's propensity to purchase crop insurance and receive disaster payments. They are assumed to be normally distributed latent variables. Crop insurance is purchased before the sowing of crop and disaster payment is generally received after the harvest of crop. Producers need to buy a minimum of catastrophic coverage of crop insurance in order to be eligible for disaster payment program. The decision to pass the disaster payment bill is ad hoc. If any ad hoc disaster payment is passed by legislation, producer would be compensated 52% of the difference between disaster payments guarantee and total farm revenue (sales revenue and indemnities from crop insurance). The following empirical results explain the effect of change in the explanatory variables on the probability of participation in crop insurance and disaster assistance payments.

Farmer's propensity to purchase crop insurance is latent and takes the value of 1(if $Y_{1i}>0$) and 0 ($Y_{1i}\leq 0$) if they are not willing to purchase the crop insurance. The probit model is used to study the effect of explanatory variables on propensity towards the purchase crop insurance. The following equation is used to explain the model:

$$Y_{1i}^{*} = xb_{1i} + \varepsilon_{1i}$$

Where

$xb_{1i} = \beta_0 + \beta_1$*age25_34 + β_2*age35_44 + β_3*agele25 + β_4*age55_64 + β_5*agegt65 + β_6* edu_2 + β_7* edu_3 + β_8* edu_4 + β_9* edu_5 + β_{10}* edu_6 + β_{11}*saleclass_2 + β_{12}* saleclass_3 + β_{13}* saleclass_4 + β_{14}* saleclass_5 + β_{15}* saleclass_6 + β_{16}* saleclass_7 + β_{17}*farmY/totalY_2 + β_{18}* farmY/totalY_3 + β_{19}* farmY/totalY_4 + β_{20}* farmY/totalY_5 + β_{21}*%ownfarm_2 + β_{22}*%ownfarm_3 + β_{23}*%ownfarm_4 + β_{24}*%ownfarm_5 + β_{25}*grains + β_{26}*oilseeds + β_{27}*cotton + β_{28}*beans + β_{29}*peanuts + β_{30}*sugar + β_{31}*tobacco + β_{32}*special + β_{33}*forages + β_{34}*premium + β_{35}*longruntemp + β_{36}*longrunppt

A farmer's propensity to receive disaster payments is unobservable and takes the value of 1(if $Y_{2i}>0$) and 0 ($Y_{2i}\leq 0$) otherwise. In order to study the effect of farmer's characteristics on propensity towards the disaster payment receipts the following equation is used to explain the model:

$Y_{2i}^{*} = xb_{2i} + \varepsilon_{2i}$

Where

$xb_{2i} = \gamma_0 + \gamma_1$*age25_34 + γ_2*age35_44 + γ_3* age45_54 + γ_4*age55_64 + γ_5*agegt65 + γ_6* edu_2 + γ_7*edu_3 + γ_8*edu_4 + γ_9*edu_5 + γ_{10}* edu_6 + γ_{11}* saleclass_2 + γ_{12}* saleclass_3 + γ_{13}* saleclass_4 + γ_{14}* saleclass_5 + γ_{15}* saleclass_6 + γ_{16}* saleclass_7 + γ_{17}* farmY/totalY_2 + γ_{18}* farmY/totalY_3 + γ_{19}* farmY/totalY_4 + γ_{20}* farmY/totalY_5 + γ_{21}*%ownfarm_2 + γ_{22}*%ownfarm_3 + γ_{23}*%ownfarm_4 + γ_{24}*%ownfarm_5 + γ_{25}*grains + γ_{26}*oilseeds + γ_{27}*cotton + γ_{28}*beans + γ_{29}*peanuts + γ_{30}*sugar + γ_{31}*tobacco + γ_{32}*special + γ_{33}*forages + γ_{34}*dum_hagcom +

γ_{35}*dum_hapcom + γ_{36}*dum_sagcom + γ_{37}*dum_sapcom + γ_{38}*drought + γ_{39}*flood + γ_{40}*longruntemp + γ_{41}*longrunppt

The stochastic error terms ε_{1i} and ε_{2i} are the errors which are assumed to be jointly standard normally distributed and rho (ρ) measures correlation between the disturbances of the equations. These terms represent effects of missing or unobserved variables that affect farmer risk management decisions and outcomes. As such, such random or unobserved factors are likely to affect both the crop insurance decision and the disaster payment outcome. If ε_{1i} and ε_{2i} are not independent, the normal probit maximum likelihood does not give consistent estimates (Maddala, 1983). Maximum likelihood procedure is one obvious way to obtain efficient parameter estimates. From the above bivariate probit model we estimated the parameters using maximum likelihood methods.

$\varepsilon_{1i} and \varepsilon_{2i}$ are normally distributed and

E (ε_{1i}) = 0

E (ε_{2i}) = 0

Var (ε_{1i}) = 1

Var (ε_{2i}) = 1

Cov (ε_{1i}, ε_{2i}) = ρ

Φ = Cumulative density function for standard bivariate normal distribution

The joint cdf of bivariate normal distribution is given as

$$\Phi_2 = \Phi(\varepsilon_1, \varepsilon_2) = \iint_{\varepsilon_1 \varepsilon_2} \Phi_2(\varepsilon_1, \varepsilon_2, \rho) d\varepsilon_1 d\varepsilon_2$$

The joint probability distribution of ($Y_{1,}$ Y_2) is written with the following four possible combinations:

$$\Pr(Y_{1i} = 1, Y_{2i} = 1) = Y_{1i}Y_{2i} \ln \Phi_2 (x_1\beta_1, x_2\beta_2, \rho)$$
$$\Pr(Y_{1i} = 1, Y_{2i} = 0) = Y_{1i}(1 - Y_{2i}) \ln[\Phi\ (x_1\beta_1 - \Phi_2 (x_1\beta_1, x_2\beta_2, \rho)]$$
$$\Pr(Y_{1i} = 0, Y_{2i} = 1) = (1 - Y_{1i})Y_{2i} \ln[\Phi\ (x_2\beta_2 - \Phi_2 (x_1\beta_1, x_2\beta_2, \rho)]$$
$$\Pr(Y_{1i} = 0, Y_{2i} = 0) = (1 - Y_{1i})(1 - Y_{2i}) \ln[(1 - \Phi\ (x_1\beta_1) - \Phi(x_2\beta_2) - \Phi_2 (x_1\beta_1, x_2\beta_2, \rho)]$$

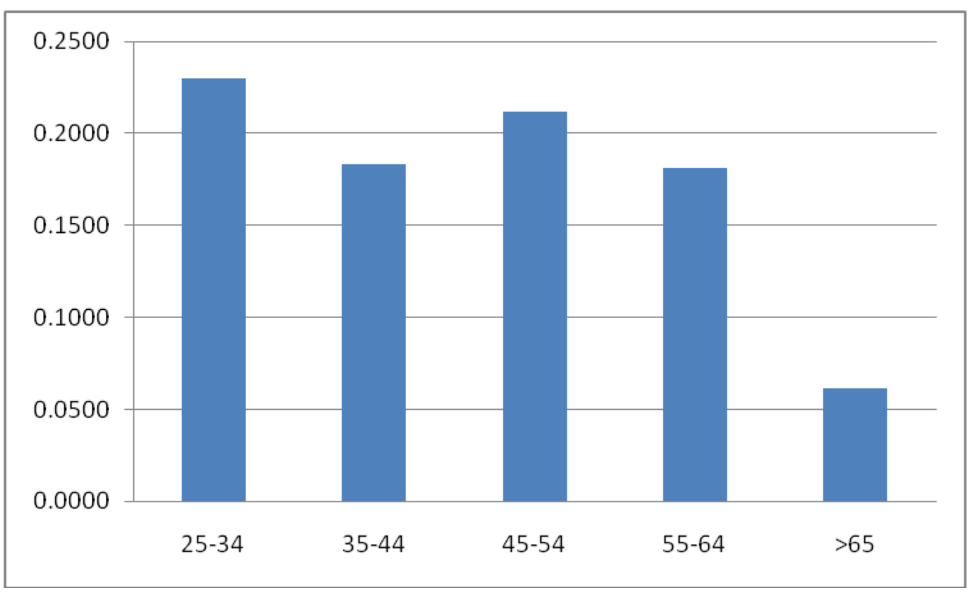
CHAPTER SIX

Results and Discussion

Analysis of Crop Insurance Participation:
Results are reported in Table 6.1
Age:

As age of farmer goes up the probability of the purchase of crop insurance goes down. Young farmers appear to be risk averse and they purchase crop insurance as a risk management tool. This variable found to be insignificant in the model individually. But the entire group variable is found to be significant based on likelihood ratio test which will be discussed in the next chapter.

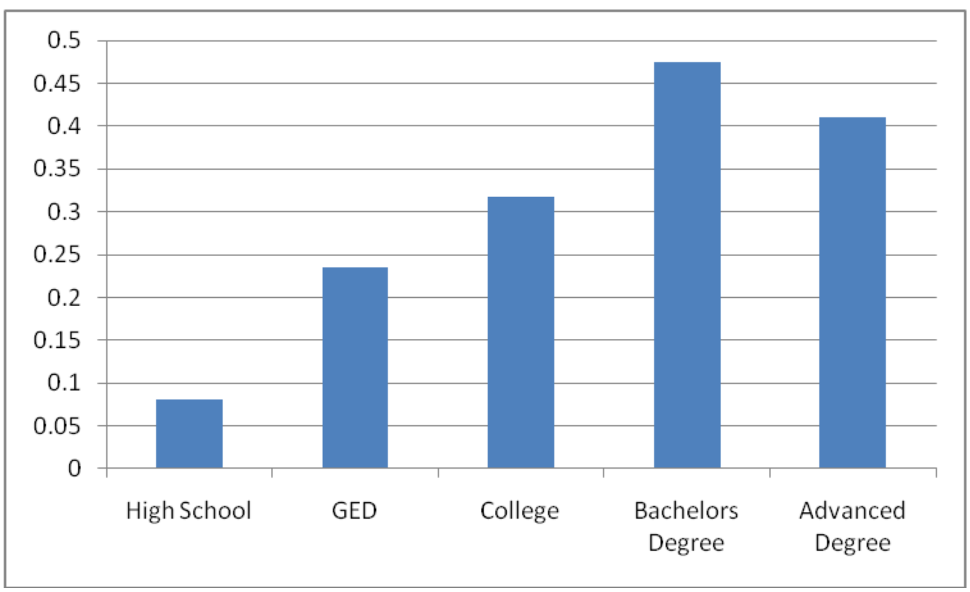
The lower age category is default and dropped from the regression. All the below estimates are in comparison with the lower age category (under 25age). As the age category moves from lower to higher the probability of purchase of crop insurance decreases. 25-34 age category has more magnitude effect compared to >65 age category.



Education:

The estimated coefficient for education has a positive sign indicating that the probability of purchasing crop insurance increases with higher education of farmer. Farmers with higher education appear to be good managers and very responsive to risk management with the purchase of crop insurance. It also suggests that high educated farmers are risk averse and consider crop insurance to be more valuable to them.

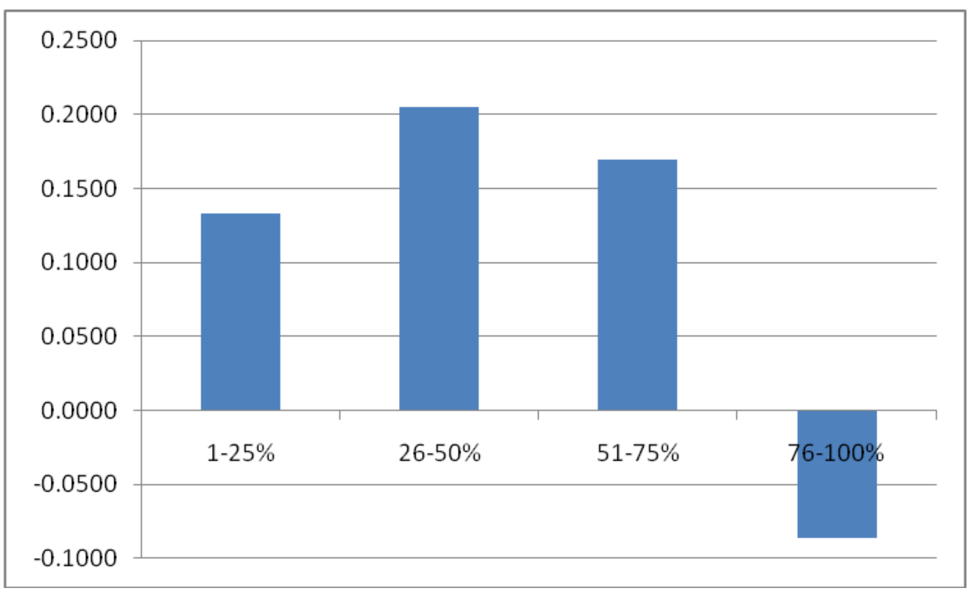
In the above graph the default category is Grade School (lowest category) and is dropped from the model. The other coefficients are in comparison with this category. We can clearly see that as the education of farmers move from High school to Bachelor's degree the magnitude of the estimates increases which suggests that farmers with higher education have more probability to purchase crop insurance.



Percentage Own farm:

The more the farmer owns the farm, the less likely he would purchase crop insurance. The demand for crop insurance is more for farmers with more rented acres. The coefficient is highly significant at 5% confidence interval. The farmers with more rented acres are found to have a positive effect on crop insurance participation. This variable is statistically significant and according to the expected sign. It could be the case the farmers with more rented acres might have more debts compared to owned farmers and there is more chance of rented farmers purchasing crop insurance due to the pressure from financial institutions.

The farmers who do not own any land is the default category. The graph below clearly shows us that demand for crop insurance is more for farmers who own 25-50% land and the demand for crop insurance is negative for farmers that own 75-100% of the land.

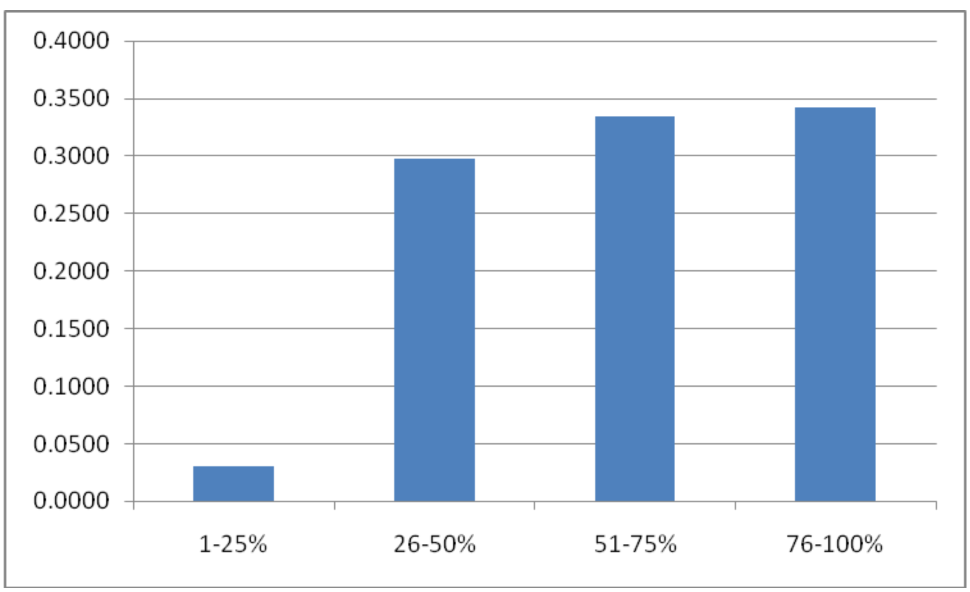


Crop Premium:

As the crop premium per acre (crop premium minus subsidies / net acres) rate increases the demand for crop insurance goes down and farmers are less inclined to insure their crops. The farmers in states with high premium rates are less likely to participate in crop insurance program. This result is consistent with the current research. The variable is significant at the 5% level.

Farm Income / Total Income:

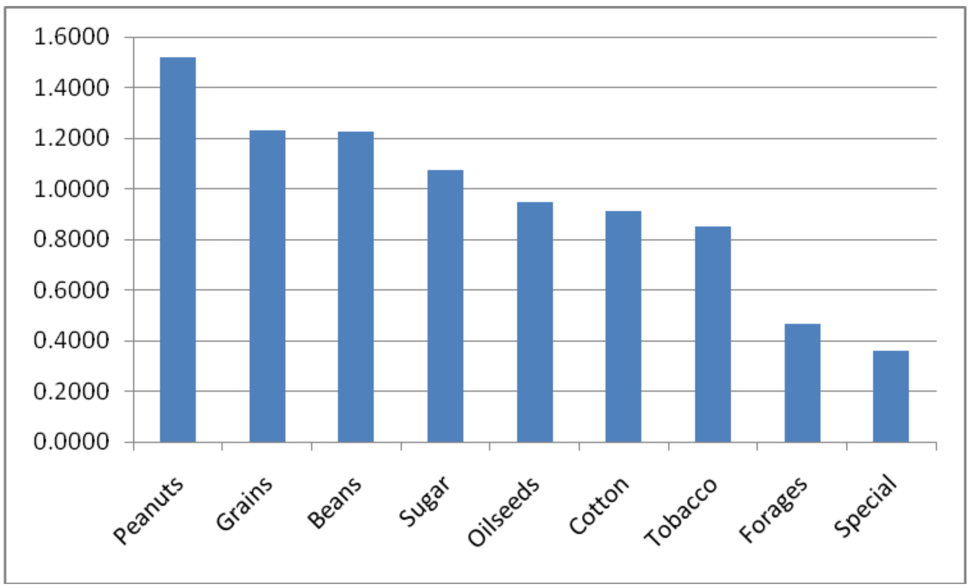
The higher the returns from the farming, the higher the probability of purchasing crop insurance. The coefficient is positive indicating that farmers with high income from farming purchase crop insurance to manage farm risk. This also suggests that producers might be highly profitable with the purchase of crop insurance.



The above graph clearly depicts as the income from farming increases from category 1-25% to 76-100% increases the demand for crop insurance. The farmers who do not earn any income from farming are the default category.

Crops:

The participation in crop insurance program by farmers varies significantly with various crops. The percent share of crop grown by the farmer is included in the model. Farmers with high percent share of peanuts, grains, pulses, sugar oilseeds and cotton are more likely to insure followed by tobacco, forage and special crops. The magnitude effect of these crops is shown in the following graph:



Corn, Soybeans, barley and wheat producers are generally insured at a high level (Glauber, 2007). This results of this study is also in accordance with above findings.

Weather Variables:

Long-run temperature is found to have a positive effect on crop insurance purchase, significant at 5% level. Long-run precipitation temperature is found to have a negative effect on crop insurance purchase, significant at 5% level. This suggests that crop insurance purchase is more likely in hotter, drier areas.

Disaster Assistance Analysis:

Results are reported in Table 6.2.

The four dummy variables that oversee the disaster relief are included in the model to see the effect of these committee members on direct disaster relief payments. Senate agricultural sub-committee has a significant positive effect at 5% on disaster payments. This positive effect suggests that state representing congressmen in disaster sub-committee receives more disaster payments compared to states without congressmen in the committee. The other three sub-committees Senate appropriation and House agricultural sub-committees are significant at 10% in the model. House appropriation sub-committee is not significant in the model.

Results suggest that a farm's probability of receiving disaster payments increases if it is in a state whose recent temperatures are above their own long run average. In other words, warmer than normal temperatures increase the likelihood of receiving disaster payments. The flood variable has a strong positive effect on disaster payments and is significant at 1% level. This implies that farmers in states with wetter than normal years are more likely to receive disaster payments. This variable captures both the fact that the state has a wetter than normal year (as measured by the Palmer Drought Index) as well as how much wetter it was. The drought variable captures both the fact that it was a drier year than normal and also measures the magnitude of the moisture deficit. As conditions approach normal, the moisture deficit declines and then drought index increases from a larger negative value towards zero. The drought variable coefficient is negative, which suggests that drought conditions increase the likelihood a farmer will receive disaster assistance.

Income variables Sale class and Farm income/Total income have a positive effect on disaster assistance. This implies that producers with high income participating in crop insurance also receive benefits from disaster payments. These variables are highly significant at 1% level.

The producers with increasing percentage of own farm receives less disaster payments and the variable is significant at 5% level.

The farmers with significant share from crops are more likely to receive disaster payments. Cattle and sheep growers are more likely to receive disaster payments whereas hog and poultry producers are less likely to receive disaster payments.

Likelihood Ratio Tests:

This test is used to evaluate the difference between the full model and restricted model and tests if the difference is statistically significant. We are using this test in our thesis to test the significance of categorical variables age, education, sale class, percentage of operated land owned, and the ratio of farm income to total household income. The test statistic calculated is twice the difference between log-likelihood of restrictive model and full model.

L.R = - 2 (ln (likelihood for restrictive model) – ln (likelihood for full model))

The above test statistic is chi-square distributed with (df1 – df2) degrees of freedom (i.e. the number of variables added to the model).

Where df1 = degrees of freedom of model1

df2 = degrees of freedom of model2

Likelihood ratio test for the categorical variables as follows:

Age:

H_0 = All age variables = 0

H_a = All age variables ≠ 0

Let L_a be maximum likelihood of the data including all variables in the model without any restrictions and L_0 be the maximum likelihood of the data without age variables in the model (restrictive model).

LR for the full model = -12915.21

LR for the restrictive model = -12925.60

L.R = - 2 (ln (likelihood for restrictive model) – ln (likelihood for full model))

L.R chi2 (10) = 20.78

Prob > chi2 = 0.0225

We reject the null hypothesis, suggesting that age is a significant factor in the model at the 5% level.

Education:

H_0 = All Education variables = 0

H_a = All Education variables ≠ 0

Let L_a be maximum likelihood of the data including all variables in the model without any restrictions and L_0 be the maximum likelihood of the data without education variables in the model (restrictive model).

LR for the full model = -12915.21

LR for the restrictive model = -12958.76

L.R = - 2 (ln (likelihood for Restrictive model) – ln (likelihood for full model))

L.R chi2 (10) = 87.1

Prob > chi2 = 0.000

We reject the null hypothesis, which implies that education variables are jointly significant in the model at the 1% level.

Sale Class:

H_0 = All Sale Class variables = 0

H_a = All Sale Class variables ≠ 0

Let L_a be maximum likelihood of the data including all variables in the model without any restrictions and L_0 be the maximum likelihood of the data without sale class variables in the model (restrictive model).

LR for the full model = -12915.21

LR for the restrictive model = -13210.76

L.R = - 2 (ln (likelihood for restrictive model) – ln (likelihood for full model))

L.R chi2 (12) = 591.10

Prob > chi2 = 0.000

We reject the null hypothesis, suggesting that sales are jointly significant at the 1% level.

Income from Farm/ Total Income:

H_0 = All Farm Income variables = 0

H_a = All Farm Income variables ≠ 0

Let L_a be maximum likelihood of the data including all variables in the model without any restrictions and L_0 be the maximum likelihood of the data without farm income variables in the model (restrictive model).

LR for the full model = -12915.21

LR for the restrictive model = -12993.87

L.R = - 2 (ln (likelihood for Restrictive model) – ln (likelihood for full model))

L.R chi2 (8) = 157.32

Prob > chi2 = 0.000

We reject the null hypothesis, suggesting that farm income share variables are significant at the 1% level.

Percentage Own Farm:

H_0 = All Own farm variables = 0

H_a = All Own farm variables ≠ 0

Let L_a be maximum likelihood of the data including all variables in the model without any restrictions and L_0 be the maximum likelihood of the data without own farm variables in the model (restrictive model).

LR for the full model = -12915.21

LR for the restrictive model = -12977.83

L.R = - 2 (ln (likelihood for Restrictive model) – ln (likelihood for full model))

L.R chi2 (8) = 125.24

Prob > chi2 = 0.000

We reject the null hypothesis, suggesting farm ownership variables are significant at the 1% level.

Measurement of Goodness of Fit

Count R-Square:

Count R-square is a measurement of goodness of fit for binary choice discrete models.

Count R-Square = Correct number of Predictions / Total number of observations.

The following table tells us the relationship between actual value of crop insurance and predicted probability values of crop insurance participation.

Table6.1: Relationship between actual and predicted values of crop insurance participation

	Actual values		
Predicted Values		0	1
	0	9244	2179
	1	880	1300

Correct count = 9244 + 1300 = 10544

Count R-Square = 10544 / 13603 = 0.7751

Adjusted Count R-Square:

This method compares how well the regression model predicts relative to a model that just predicts all outcomes to be the most common outcome. For example if we know that an event occurs in 60% of the observations, a naïve prediction that the event occurs for each individual observation will be correct 60% of the time. The adjusted count R square measures how much better the regression model predicts than the naïve model.

Adjusted Count R-square =

(Correct number of predictions – n) / (Total number of observations – n)

Where n is the mode or the most frequent outcome.

From the above table:

Adjusted Count R-square = (10544 – 10124) / (13603 – 10124) = 0.12

Conclusions

This study used farm-level data from 27 U.S. to examine which factors influence farmer crop insurance program participation and receipt of disaster payments. Using a bivariate probit model some main findings are as follows.

The probability of participating in federal crop insurance programs is

(a) lower for farmers more than 65 years of age

(b) increasing with farmer education level

(c) increasing with agricultural sales

(d) lower for farms where farm sales are a small share of household income

(e) higher in states with higher average temperatures and lower average precipitation

The probability of receiving disaster payments is

(a) increase as farms depend more on farm income for their total household income

(b) increases with sales in peanut farming and cattle ranching

(c) is greater if a farmer is in a state with a senator on the agricultural appropriations committee (one of the committees that votes on disaster payments)

(d) greater in states experiencing drier or wetter than normal hydrologic conditions

(e) greater in states experiencing warmer than normal year

This present study considered how the equations for crop insurance and disaster payments are linked through the regression error terms. The bivariate probit specification was analogous to a seemingly unrelated regression for continuous variables. Future research could also explore how disaster payments influence crop insurance choice and vice versa. Some studies have specified models where disaster payments influence insurance decisions (Anderson, Barnett and Coble, 2008; Garrett et al., 2006). In contrast, Goodwin and Rejesus (2008) assume the direction of causality goes in the other direction. Crop insurance choice affects disaster payments, but not vice versa.

A possible area of future research would be to consider these equations as simultaneous, where the possibility that disaster payments and insurance affect each other. In my future research on this topic, I intend to use Simultaneous bivariate probit model expecting that crop insurance purchase and disaster payments are endogenous to each other. Economic variables like loss ratio, crop premium rates, farm debts, APH yields, average yield at farm level would give more conclusive results to this thesis. Methods such as those developed by Aradhyula and Tronstad (2003) could be applied to the problem.

Policy Implications:

Knowing the characteristics of farmers will help the private insurance companies to target the farmers with the desirable characteristics and improve their business. This will help the insurance companies to bring more farmers in to their business who are not holding any insurance policies.

Table: 6.1

Dependent Variable: Crop Insurance

	Specification: 1		**Specification: 2**	
Variable	**Estimate**	**Std.Error**	**Estimate**	**Std.Error**
Age25_34	0.2300	0.3140	0.2005	0.3189
Age35_44	0.1835	0.3088	0.1591	0.3138
Age45_54	0.2119	0.3078	0.1856	0.3128
Age55_64	0.1810	0.3080	0.1625	0.3130
Agegt65	0.0616	0.3088	0.0399	0.3138
Edu_2	0.0813	0.1306	0.0970	0.1329
Edu_3	0.2345*	0.1062	0.2429*	0.1080
Edu_4	0.3174**	0.1068	0.3248**	0.1086
Edu_5	0.4754**	0.1076	0.4849**	0.1095
Edu_6	0.4109**	0.1143	0.4254**	0.1162
SaleClass_2	0.5803**	0.0637	0.5613**	0.0643
SaleClass_3	0.8686**	0.0682	0.8459**	0.0686
SaleClass_4	1.0619**	0.0681	1.0426**	0.0685
SaleClass_5	1.1507**	0.0738	1.1355**	0.0743
SaleClass_6	1.1483**	0.0816	1.1369**	0.0821
SaleClass_7	1.0264**	0.0907	1.0193**	0.0913
Farm Y/Total Y_2	0.0306	0.0955	0.0156	0.0970
Farm Y/Total Y_3	0.2975**	0.0976	0.278**	0.0990
Farm Y/Total Y_4	0.3339**	0.0982	0.3139**	0.0997
Farm Y/Total Y_5	0.3424**	0.0956	0.3101**	0.0972
%Ownfarm_2	0.1327*	0.0607	0.1272*	0.0609
%Ownfarm_3	0.2051**	0.0606	0.1956**	0.0607
%Ownfarm_4	0.1698**	0.0617	0.1542*	0.0619
%Ownfarm_5	-0.0865	0.0563	-0.0889	0.0566
Grains	1.2313**	0.0905	1.1238**	0.0896
Oilseeds	0.9478**	0.1157	0.9547**	0.1171
Cotton	0.9139**	0.1404	0.7604**	0.1384
Beans	1.2281**	0.3289	1.25**	0.3278
Peanuts	1.5220**	0.3277	1.482**	0.3311
Sugar	1.0753**	0.3302	1.0692**	0.3335
Tobacco	0.8535**	0.2368	0.7102**	0.2354

Special	0.3597**	0.1003	0.1907*	0.0940
Forages	0.4687**	0.1148	0.3098**	0.1171
Premium	-1.7912*	0.8282	-0.042**	0.0068
Longruntemp	0.0083*	0.0038	0.0121**	0.0039
Longrunppt	-0.1951**	0.0215	-0.2065**	0.0217
Constant	-2.8026	0.4299	-2.9598	0.4364

Table: 6.2

Dependent Variable: Disaster Assistance

Variable	Specification: 1 Estimate	Specification: 1 Std.Error	Specification: 2 Estimate	Specification: 2 Std.Error
Age25_34	0.4067	0.3114	0.4055	0.3114
Age35_44	0.4056	0.3070	0.4040	0.3070
Age45_54	0.3570	0.3059	0.3552	0.3060
Age55_64	0.3234	0.3062	0.3221	0.3062
Agegt65	0.2949	0.3068	0.2933	0.3068
Edu_2	0.2765*	0.1171	0.2763*	0.1170
Edu_3	0.2864**	0.0970	0.2863**	0.0970
Edu_4	0.3362**	0.0976	0.3359**	0.0976
Edu_5	0.2651**	0.0988	0.265**	0.0987
Edu_6	0.2575*	0.1048	0.2567*	0.1048
SaleClass_2	0.5739**	0.0493	0.5744**	0.0493
SaleClass_3	0.7062**	0.0557	0.7069**	0.0557
SaleClass_4	0.7874**	0.0555	0.7882**	0.0555
SaleClass_5	0.7844**	0.0624	0.7855**	0.0624
SaleClass_6	0.7475**	0.0714	0.7489**	0.0714
SaleClass_7	0.5292**	0.0814	0.5305**	0.0814
Farm Y/Total Y_2	0.0260	0.0759	0.0253	0.0759
Farm Y/Total Y_3	0.2905**	0.0804	0.2902**	0.0804
Farm Y/Total Y_4	0.4449**	0.0813	0.4446**	0.0813
Farm Y/Total Y_5	0.4613**	0.0784	0.4608**	0.0784
%Ownfarm_2	0.1778**	0.0579	0.1777**	0.0579
%Ownfarm_3	0.1578**	0.0579	0.1575**	0.0579
%Ownfarm_4	0.2125**	0.0582	0.2119**	0.0582
%Ownfarm_5	-0.0043	0.0524	-0.0043	0.0525
Grains	0.7726**	0.0764	0.7711**	0.0763
Oilseeds	0.1945	0.1107	0.1910	0.1107
Cotton	0.6794**	0.1236	0.6772**	0.1235
Beans	1.5605**	0.3298	1.5613**	0.3299
Peanuts	1.2329**	0.3030	1.2277**	0.3026
Sugar	0.1955	0.3279	0.1891	0.3290
Tobacco	0.8514**	0.1964	0.8518**	0.1964

Special	0.4641**	0.0768	0.4632**	0.0767
Forages	0.3358**	0.0966	0.3345**	0.0965
Dum_hagcom	0.0609*	0.0378	0.0604	0.0380
Dum_hapcom	-0.0059	0.0326	-0.0046	0.0326
Dum_sagcom	0.2806**	0.0421	0.2748**	0.0424
Dum_sapcom	0.0027	0.0293	0.0004	0.0293
Drought	-0.0608**	0.0212	-0.0629**	0.0212
Flood	0.0588**	0.0143	0.0603**	0.0143
Longruntemp	-0.0029	0.0039	-0.0029	0.0039
Longrunppt	-0.0153	0.0279	-0.0131	0.0279
/athrho	0.4756	0.0183	0.4708	0.0184
Rho	0.4427	0.0147	0.4388	0.0148

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Variable Definitions:

Variable	Description
INSURANCE	Binary variable representing whether farmer participated in Crop insurance (1 = if farmer participated, 0 = otherwise)
DISASTER	Binary variable representing whether farmer received disaster Assistance (1= if farmer received disaster assistance, 0 = otherwise)
AGE	Age of the farmer
EDU	Education of the farmer
SALE CLASS	Annual market value of the agricultural products sold from farm or ranch
FARM Y/ TOTAL Y	Percentage of Income earned from farming to the total income
%OWN FARM	Percentage of land owned by farmer
COTTON	Percentage of total farm crop acres planted to Cotton
GRAINS	Percentage of total farm crop acres planted to Grains
SOYBEANS	Percentage of total farm crop acres planted to Soybeans
BEANS	Percentage of total farm crop acres planted to Beans
PEANUTS	Percentage of total farm crop acres planted to Peanuts
SUGAR	Percentage of total farm crop acres planted to sugar
TOBACCO	Percentage of total farm crop acres planted to tobacco
SPECIAL	Percentage of total farm crop acres planted to special crops

OTHCROPS	Percentage of total farm crop acres planted to other crops
AQUA	Percentage of total farm from aquaculture
CATTLE	Percentage of total farm from cattle
DAIRY	Percentage of total farm from dairy
HOGS	Percentage of total farm from hogs
SHEEP	Percentage of total farm from sheep
POULTRY	Percentage of total farm from poultry
PREMIUM	Premium per acre [(Premium – Subsidies)/Net acres] of the state
INT_PREM_ DIVERSE	Interaction of Premium*Diversification
DIVERSIFIC ATION	Herfindahl Index
LONGRUN TEMP	Average temperature from Jan1975 to Dec2005
LONGRUN PPT	Average precipitation from Jan1975 to Dec2005
DROUGHT Hydrological	Captures deviation from normal annual average of Palmers Drought Index (PHDI) for year 2005. Calculated as min [PHDI, 0]
FLOOD Hydrological	Captures deviation from normal annual average of Palmers Drought Index (PHDI) for year 2005. Calculated as max [PHDI,0]
DIFF_TEMP	Average annual temperature of 2005 minus lonruntemp
DUM_HAGCOM representative	Dummy variable which is equal to one if the state has a in House Agricultural Committee (109th Congress), 0 otherwise
DUM_HAPCOM representative	Dummy variable which is equal to one if the state has a

in House Appropriation Committee (109th Congress), 0 otherwise

DUM_SAGCOM Dummy variable which is equal to one if the state has a representative in Senate Agricultural Committee (109th Congress), 0 otherwise

DUM_SAPCOM Dummy variable which is equal to one if the state has a representative in Senate Appropriation Committee (109th Congress), 0 otherwise

Characteristics of farmers Response (Farmers % Response rate in the survey):

Farmers Characteristics	**% of Response**
Crop Insurance Participation	25.58%
Disaster Assistance Received	29.63%
Age less than 25	0.23%
Age between 25 – 34	3.40%
Age between 35 – 44	12.56%
Age between 45 – 54	30.34%
Age between 55 – 64	28.98%
Age greater 65	24.50%
SaleClass1 (Under $10,000)	21.20%
SaleClass2 ($10,000 - $49,999)	19.44%
SaleClass3 ($50,000 - $99,999)	15.08%
SaleClass4 ($100,000 - $249,999)	23.53%
SaleClass5 ($250,000 - $499,999)	11.20%
SaleClass6 ($500,000 - $999,999)	5.70%
SaleClass7 ($1,000,000 and above)	3.86%
Farm Income / Total Income_1 (None)	4.59%
Farm Income / Total Income_2 (1 – 25%)	27.97%
Farm Income / Total Income_3 (26 – 50%)	13.67%
Farm Income / Total Income_4 (51 – 75%)	13.34%

Farm Income / Total Income_5 (76 – 100%)	40.42%
Edu_1 (Grade School)	2.03%
Edu_2 (Some High School)	3.50%
Edu_3 (GED)	28.37%
Edu_4 (Some College / Tech School)	31.74%
Edu_5 (College Bachelor’s Degree)	24.26%
Edu_6 (College Advanced Degree)	10.10%
%Ownfarm1 (None)	6.15%
%Ownfarm2 (1 - 25%)	12.86%
%Ownfarm3 (26 - 50%)	13.34%
%Ownfarm4 (51 - 75%)	12.67%
%Ownfarm5 (76 - 100%)	54.99%

State level data:

STATE	% Observations with crop insurance	% Observations with disaster payments	Flood Avg.	Drought Avg.	Long run Precipitation Average	Long run Temperature Average
ILLINOIS	37.31	16.92	0	-1.0733	3.238	51.8543
IOWA	42.53	18.14	0.5542	0	2.7955	47.9745
KANSAS	45.54	46.79	2.725	0	2.3803	54.4508
MICHIGAN	30.42	34.66	0	-1.1375	2.7411	44.6129
MISSOURI	25.58	35.48	0.4325	0	3.5058	54.5516
NEBRASKA	45.27	45.45	0.3683	0	1.9493	49.0073
OHIO	28.84	23.66	3.2792	0	3.3037	50.8113
SOUTHDAKOTA	46.1	59.1	1.2025	0	1.6848	45.3879
WISCONSIN	16.57	22.14	0	-0.525	2.717	43.3651
MARYLAND	13.18	9.55	1.67	0	3.7131	54.3366
NEWJERSEY	9.92	9.16	1.2492	0	3.8909	52.7616
NEWYORK	13.54	17.29	2.6833	0	3.4954	45.507
PENNSYLVANIA	20.6	15.86	2.775	0	3.5999	48.8546
VERMONT	9.84	15.98	3.2267	0	3.5759	42.897
ALABAMA	15.66	26.77	2.73	0	4.8587	62.8081
FLORIDA	13.36	36.87	2.3017	0	4.6418	70.7406
GEORGIA	14.9	25	2.895	0	4.2074	63.5325
NORTHCAROLINA	11.96	24.26	0.8642	0	4.169	59.0761
TEXAS	31.11	43.03	2.0217	0	2.3933	64.9597
ARIZONA	16.84	16.49	3.9625	0	1.1273	60.7148
COLORADO	33.88	46.34	1.1633	0	1.3262	45.5632
IDAHO	17.92	27.36	0.3875	0	1.5524	44.6349
MONTANA	41.36	55.53	0	-3.0775	1.2669	42.9605
OREGON	12.98	16.6	0	-0.4742	2.241	48.6247
UTAH	12.22	24.89	4.8758	0	1.0234	48.978
WASHINGTON	23.23	29.67	0	-1.66	3.151	48.514
WYOMING	23.26	42.25	0	-2.37	1.0569	42.2379