

A Bivariate Probit Model of Disaster Assistance and Crop Insurance
Participation

by

Pavan Kumar Reddy Dhanireddy


A Thesis submitted to the faculty of the
DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS
In Partial Fulfillment of the Requirements
For the Degree of
MASTER OF SCIENCE
In the Graduate College
THE UNIVERSITY OF ARIZONA

2010

STATEMENT BY AUTHOR

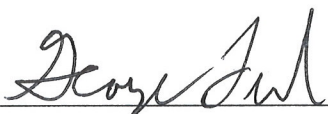
This thesis has been submitted in partial fulfillment of requirements for an advanced degree at the University of Arizona.

Brief quotations from this thesis are allowable without special permission, provided that accurate acknowledgement of source is made. Requests for permissions for extended quotation form or reproduction of this manuscript in whole or in part may be granted by the head of the major department or the Dean of the Graduate College when in his or her the proposed use of the material is in the interest of scholarship. In all other instances, however, permission must be obtained from the author.

SIGNED: 

APPROVAL BY THESIS DIRECTOR

This Thesis has been approved on the dates shown below



George Frisvold
Professor of Agricultural and Resource Economics

7/30/2010

Date

ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. George Frisvold for his constructive guidance, illuminating comments, and sincere encouragement throughout this study. His vast knowledge and student-friendly approach along with his close supervision have established a continuous, strong stream of information that has made this thesis possible.

I would also like to express gratitude to my committee members, Dr. Russell Tronstad, and Dr. Tauhid Rahman for providing me invaluable insight into different aspects of this study.

I would especially like to thank Dr. Russell Tronstad for generously providing the data used in this thesis and express my heartfelt gratitude to Dr. Satheesh Aradhyula for his expert and valuable suggestions. I would also like to thank the Department of Agricultural and Resource Economics for providing me with an opportunity to pursue the Master program.

I would like to express my sincere thanks to all my family and friends at the AREC for encouraging me and providing useful thought when needed.

Table of Contents

List of Figures	6
List of Tables	7
Abstract	8
Chapter 1. Introduction	9
Background	10
Chapter 2. Literature Review	12
Chapter 3. Description of Data and Regression Variables	
Description of Data	15
Description of Regression Variables	16
Chapter 4. Measure of Association of Contingency Tables	23
Chapter 5. Econometric Model	33
Chapter 6. Results and Discussion	
Analysis of Crop Insurance Participation	38
Disaster Assistance Analysis	46
Marginal effects	49
Likelihood Ratio test.....	51
Measurement of goodness of fit.....	54
Conclusions.....	56
References	64

Appendix

Basic Definitions.....	66
Variable Definitions.....	69
Characteristics of farmers response	72
State level data	74

List of Figures

Fig 6.1: Effect of education on crop insurance participation.....	39
Fig 6.2: Effect of percentage of operated land owned on crop insurance participation	40
Fig 6.3: Effect of farm income/total income on crop insurance participation	41
Fig 6.4: Effect of sale class on crop insurance participation	42
Fig 6.5: Effect of crop sales shares on crop insurance participation	43
Fig 6.6: Effect of livestock sales on crop insurance participation	44
Fig 6.7: Estimates of regional variables on crop insurance participation.....	45
Fig 6.8: Effect of crop shales shares on disaster assistance.....	47
Fig 6.9: Effect of livestock on disaster assistance	47

List of Tables

Table 3.1, Classification of Age	16
Table 3.2, Classification of Education	17
Table 3.3, Classification of Sales Class	18
Table 3.4, Classification of Farm Income as a Share of Total Household Income	18
Table 3.5, Classification of % Own Farm.....	19
Table 4.1, Relationship between Sale Class and Crop Insurance Participation.....	24
Table 4.2, Relationship between Age and Crop Insurance	28
Table 4.3, Relationship between Farm Income / Total Income and Crop Insurance.....	29
Table 4.4, Relationship between Percentage of Own Farm and Crop Insurance	30
Table 4.5, Relationship between Crop Insurance Participation and Disaster Assistance.....	30
Table 4.6, Relationship between Diversification and Farm Income / Total Income	31
Table 6.1, Relationship between Actual and Predicted Values of Crop Insurance	55
Table 6.2, Factors affecting the Crop Insurance Participation.....	58
Table 6.3, Factors affecting the Disaster Payments	60
Table 6.4, Marginal effects of Factors Affecting Crop Insurance Participation.....	62
Table 6.5, Marginal effects of Factors Affecting Disaster Payments	63

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 analysts 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.

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:

$(\text{State Crop Premium} - \text{Total Subsidy received by state}) / \text{Net Acres of state}.$

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

Regional Dummy Variables:

This variable is included in the model to capture the regional effect on crop insurance purchase and disaster payments. The given 27 states are divided in to 4 regions namely Northeast, Midwest, South and West based on the classification of the U.S. Census. Each region is coded as a dummy variable and takes the value of 1 if the state belongs to that region and 0 otherwise.

Classification of states as follows:

Northeast: New Jersey, New York, Pennsylvania and Vermont

Midwest: Illinois, Ohio, Iowa, Kansas, Michigan, Missouri, Nebraska, South Dakota and Wisconsin

South: Alabama, Florida, Georgia, Maryland, North Carolina, Texas

West: Arizona, Colorado, Idaho, Montana, Oregon, Utah, Washington, Wyoming

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.

Difference in temperature (DIFF TEMP):

This variable is calculated as the difference between 2005 annual average temperature and 30-year average temperature (1975-2005).

Diversification (Herfindahl Index):

This variable is included to measure the degree of specialization in crop acreage production. It is calculated as sum of squares of all crops and livestock grown by the producers. This variable ranges from 0 to 1. Herfindahl index takes the value of 1 if the farmer produces only one crop. The value of 1 means a farm is completely specialized in one crop, while lower values represent more diversification. One might expect that production diversification might substitute for crop insurance or less risk of disaster losses.

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.

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

$\gamma = 0$ 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:

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

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

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

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

$$658 * (446 + 360) = 530,348$$

$$329 * 360 = 118,440$$

$$\text{Sum of above discordant pairs} = 615468 + 2120352 + 2166395 + 2059904 + 530348 + 118440 = 7,610,907$$

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

$$\gamma = (22,389,956 - 7,610,907) / (22,389,956 + 7,610,907)$$

$$\gamma = 0.4926$$

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

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

$$\gamma = (11026606 - 15403139) / (11026606 + 15403139)$$

$$\gamma = - 0.1655$$

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

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

$$\gamma = (18504616 - 7163674) / (18504616 + 7163674)$$

$$\gamma = 0.4418$$

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:

	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:

	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
$.25 \leq$ Diversification $<.5$	86	582	347	390	1206
$.5 \leq$ Diversification $<.75$	150	1117	593	593	1717
$.75 \geq$ 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 farmer received disaster payments and 0 otherwise. Probit model were used to study the economic factors influencing the crop insurance purchase and disaster payment outcomes.

$$P(Y = 1 | X) = \Phi(X\beta)$$

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.

$$Y_i = 1 \text{ if } Y_i^* > 0$$

$$Y_i = 0 \text{ if } Y_i^* \leq 0$$

Where $Y_i \sim N(0, 1)$ 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:

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

Where

$$\begin{aligned}
xb_{1i} = & \beta_0 + \beta_2*agele25 + \beta_3*age25_34 + \beta_4*age35_44 + \beta_5*age55_64 + \beta_6*agegt65 + \\
& \beta_7* edu_1 + \beta_8* edu_2 + \beta_9* edu_3 + \beta_{10}* edu_5 + \beta_{11}* edu_6 + \beta_{12}*saleclass_1 + \beta_{13}* \\
& saleclass_2 + \beta_{14}* saleclass_3 + \beta_{15}* saleclass_5 + \beta_{16}* saleclass_6 + \beta_{17}* saleclass_7 + \\
& \beta_{18}*farmY/totalY_1 + \beta_{19}* farmY/totalY_2 + \beta_{20}* farmY/totalY_3 + \beta_{21}* \\
& farmY/totalY_4 + \beta_{22}*%ownfarm_1 + \beta_{23}*%ownfarm_2 + \beta_{24}*%ownfarm_3 + \\
& \beta_{25}*%ownfarm_4 + \beta_{26}*oilseeds + \beta_{27}*cotton + \beta_{28}*pulses + \beta_{29}*peanuts + \beta_{30}*sugar + \\
& \beta_{31}*tobacco + \beta_{32}*special + \beta_{33}*forages + \beta_{34}*othcrops + \beta_{35}*aqua + \beta_{36}*cattle + \\
& \beta_{37}*dairy + \beta_{38}*hogs + \beta_{39}*sheep + \beta_{40}*poultry + \beta_{41}*premium + \beta_{42}*diversification + \\
& \beta_{43}*int_prem_diverse + \beta_{44}*longruntemp + \beta_{45}*longrunppt + \beta_{46}*dum_midwest + \\
& \beta_{47}*dum_northeast + \beta_{48}*dum_west
\end{aligned}$$

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

$$\begin{aligned}
xb_{2i} = & \gamma_0 + \gamma_2* agele25 + \gamma_3*age25_34 + \gamma_4*age35_44 + \gamma_5*age55_64 + \gamma_6*agegt65 + \gamma_7* \\
& edu_1 + \gamma_8*edu_2 + \gamma_9*edu_3 + \gamma_{10}*edu_5 + \gamma_{11}* edu_6 + \gamma_{12}* saleclass_1 + \gamma_{13}* \\
& saleclass_2 + \gamma_{14}* saleclass_3 + \gamma_{15}* saleclass_5 + \gamma_{16}* saleclass_6 + \gamma_{17}* saleclass_7 + \\
& \gamma_{18}* farmY/totalY_1 + \gamma_{19}* farmY/totalY_2 + \gamma_{20}* farmY/totalY_3 + \gamma_{21}* \\
& farmY/totalY_4 + \gamma_{22}*%ownfarm_1 + \gamma_{23}*%ownfarm_2 + \gamma_{24}*%ownfarm_3 + \\
& \gamma_{25}*%ownfarm_4 + \gamma_{26}*oilseeds + \gamma_{27}*cotton + \gamma_{28}*pulses + \gamma_{29}*peanuts + \gamma_{30}*sugar +
\end{aligned}$$

$$\begin{aligned}
& \gamma_{31}*\text{tobacco} + \gamma_{32}*\text{special} + \gamma_{33}*\text{forages} + \gamma_{34}*\text{othcrops} + \gamma_{35}*\text{aqua} + \gamma_{36}*\text{cattle} + \\
& \gamma_{37}*\text{dairy} + \gamma_{38}*\text{hogs} + \gamma_{39}*\text{sheep} + \gamma_{40}*\text{poultry} + \gamma_{41}*\text{dum_hagcom} + \gamma_{42}*\text{dum_hapcom} + \\
& \gamma_{43}*\text{dum_sagcom} + \gamma_{44}*\text{dum_sapcom} + \gamma_{45}*\text{drought} + \gamma_{46}*\text{flood} + \gamma_{47}*\text{longruntemp} + \\
& \gamma_{48}*\text{longrunppt} + \gamma_{49}*\text{diff_temp} + \gamma_{50}*\text{dum_midwest} + \gamma_{51}*\text{dum_northeast} + \\
& \gamma_{52}*\text{dum_west}
\end{aligned}$$

The stochastic error terms ε_{1i} and ε_{2i} are the errors which are assumed to be jointly standard normally distributed and ρ (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.

ε_{1i} and ε_{2i} are normally distributed and

$$E(\varepsilon_{1i}) = 0$$

$$E(\varepsilon_{2i}) = 0$$

$$\text{Var}(\varepsilon_{1i}) = 1$$

$$\text{Var}(\varepsilon_{2i}) = 1$$

$$\text{Cov}(\varepsilon_{1i}, \varepsilon_{2i}) = \rho$$

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:

The bivariate probit regression estimates of explanatory variables along with standard errors and their significance are shown in **Table 6.2**. The analysis of results is discussed in the following section:

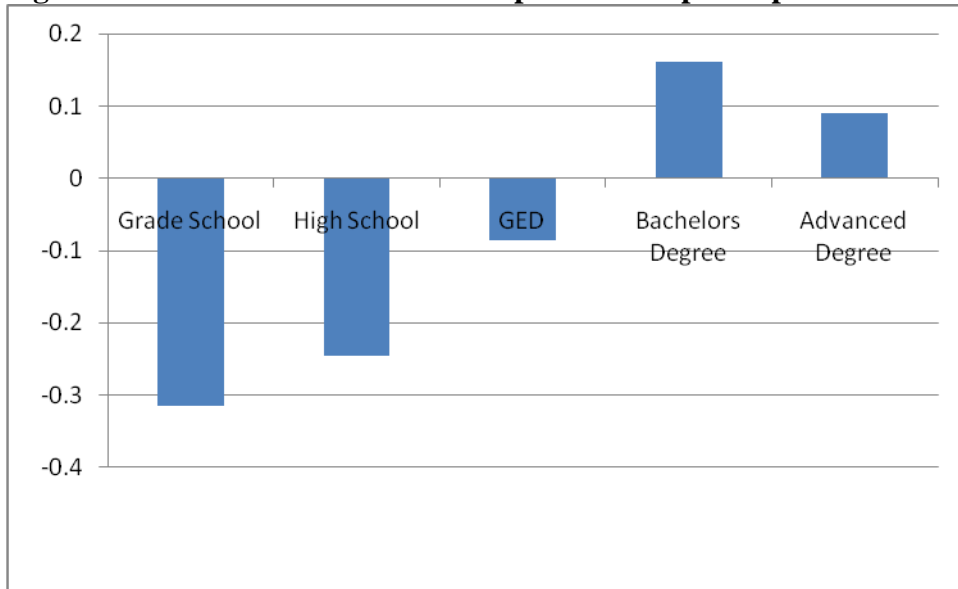
Age:

The age category of 45-54 is default (mode) and dropped from the regression. The only category parameter that was statistically significant was for the >65 age category. This parameter was negative, suggesting that the oldest category of farmers were less likely to purchase crop insurance. This finding is in consistent with the study of Black and Dorfman (2000).

Education:

Some college/ Edu_4 was the most frequent category (mode) in the education group and excluded as the default in the model. The results suggest that the probability of purchasing insurance increases with education. Coefficients for categories representing less education than the default were negative and significant, while those for categories representing more education than the default were positive.

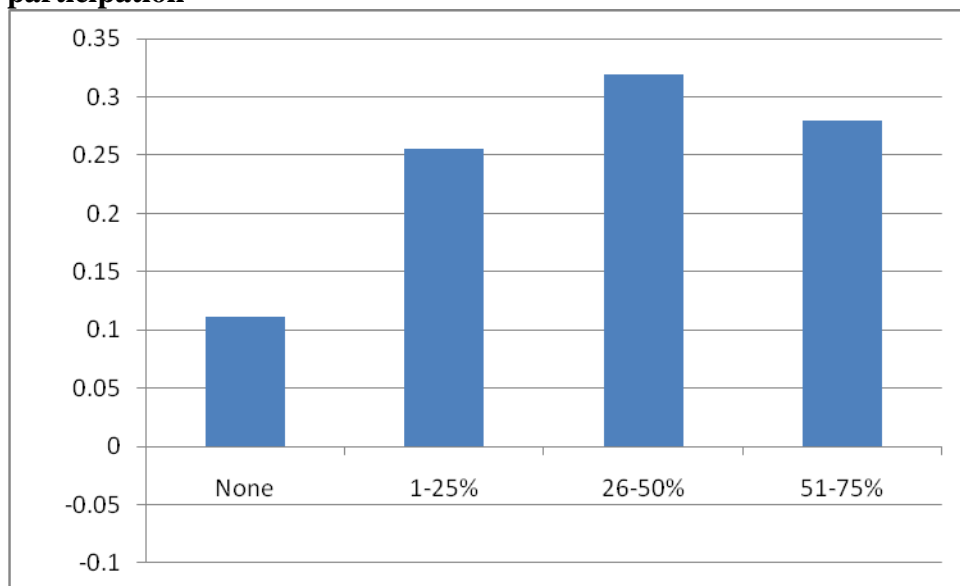
We can clearly see that as the education of farmers move from grade school to advanced degree the magnitude of the estimates increases, which suggests that farmers with higher education have a higher probability of purchasing crop insurance. This result is consistent with earlier findings by Sherrick et al.(2004) and Smith and Baquet (1996).

Figure 6.1: Effect of education on crop insurance participation**Percentage Own Farm:**

A farmer who owns 75-100% land operated is the most frequent and default category.

The coefficients for all the other categories are significant and positive. This suggests that farmers with the highest share of land owned are less likely to have crop insurance.

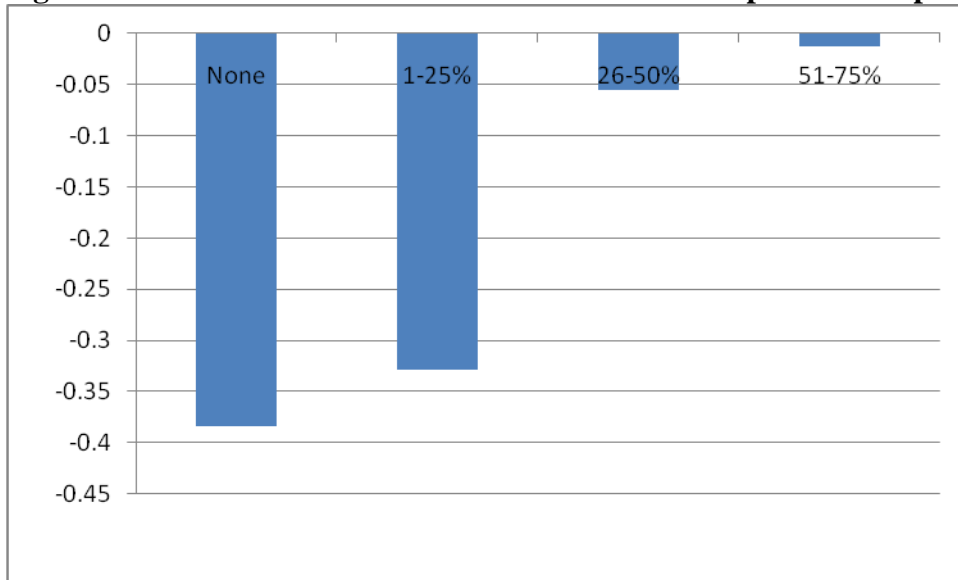
Figure 6.2: Effect of the percentage of operated land owned on crop insurance participation



Farm Income / Total Income:

A farmer with 75-100% of his or her household income coming from farming is the most frequent and the default category. Farms with a low ratio of farm to total income are less likely to have crop insurance. The coefficients for the two lowest share groups (none, and 1 – 25%) are negative and significant. The coefficients for the middle categories were negative, but insignificant. This suggests that as households specialize in farming as their source of income, they are more likely to have crop insurance. In contrast, where farming is a relatively minor share of household income, households are less likely to have crop insurance.

Figure 6.3: Effect of farm income / total income on crop insurance participation



These results are in consistent with the study of Black and Dorfman (2000).

Sale Class:

Producers with lower sale class (saleclass_1 – saleclass_3) have a negative effect on crop insurance participation compared with default saleclass_4 category. Coefficients for the other sales classes are not statistically significant.

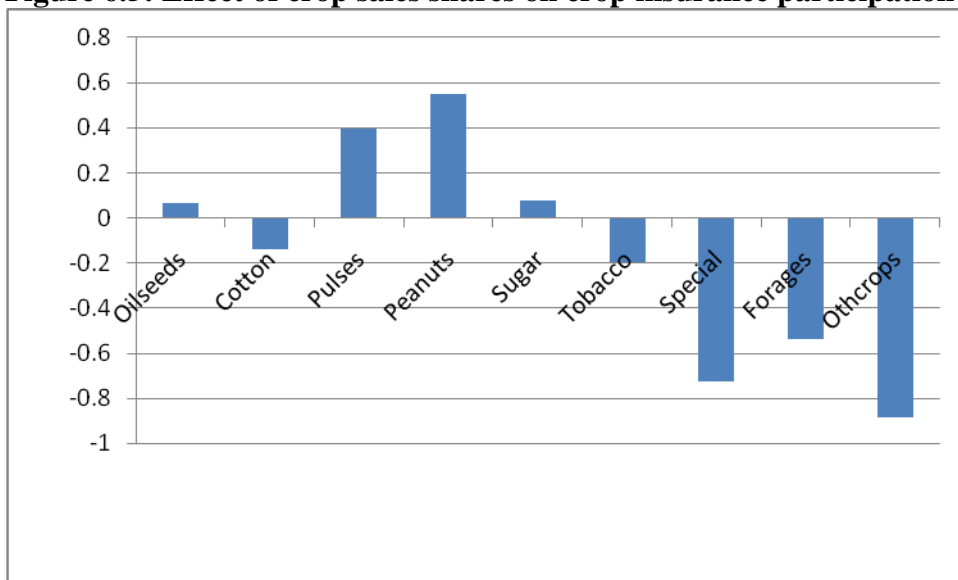
Figure 6.4: Effect of sale class on crop insurance participation



Crops:

The participation in crop insurance program by farmers varies significantly with the share of sales in different crops. The share of farm sales from grains is the default share, dropped from the model. Farmers with a high percent share of peanuts, sugar and oilseeds are more likely to insure. Farmers with a high percent share from other crops, special crops, forages, tobacco and cotton are less likely to insure their crops. The magnitude of the effect of these crops is shown in the following graph:

Figure 6.5: Effect of crop sales shares on crop insurance participation

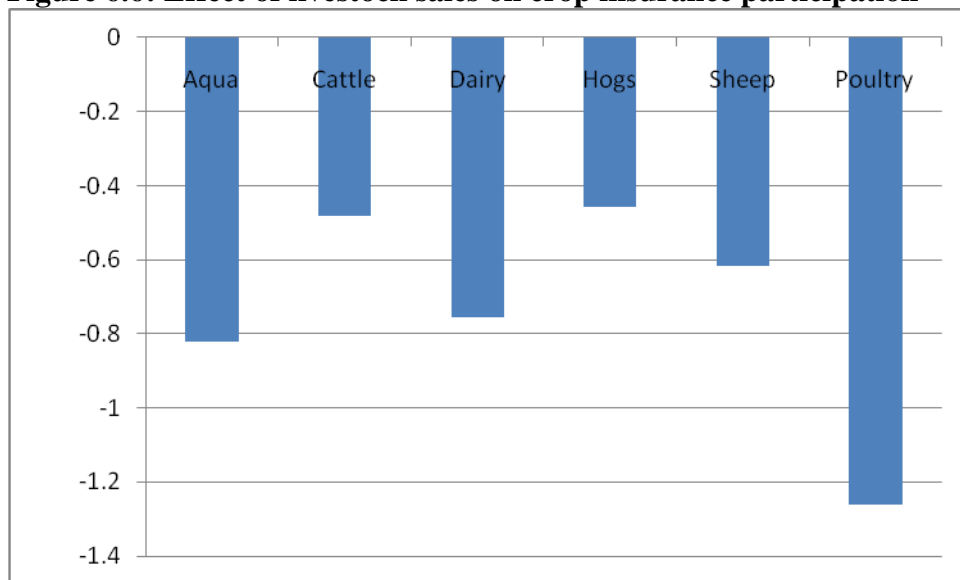


All the above variables are in comparison with the share of grains in total sales, which is default and dropped from the model.

Livestock:

The producers with significant share of poultry, aquaculture, dairy, sheep, cattle and hogs are less inclined to participate in crop insurance program. This suggest that producers might be engaged in both crop production and livestock to reduce the risk and for stabilisation of income by diversification, thereby reducing the demand for crop insurance.

Figure 6.6: Effect of livestock sales on crop insurance participation



All the above variables are significant at 1% level. This result is consistent with the finding of Sherrick et al. (2004).

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. The coefficient, although it has the expected sign, is not significant.

Interaction of Premium*Diverse:

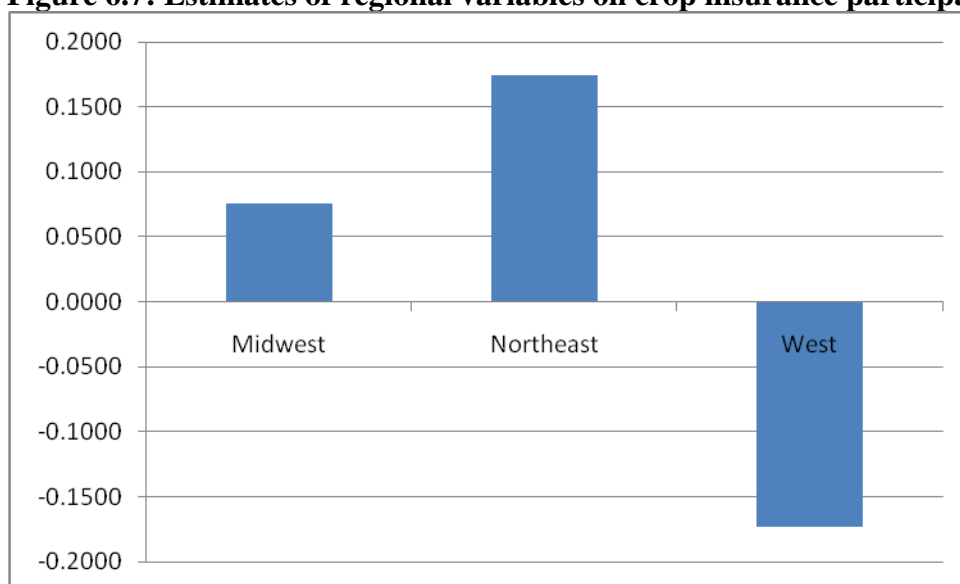
Having more diversified sales did not have a statistically significant effect. Nor was the interaction between diversification and premium rate significant.

Regional Variables:

Four regional dummy variables are included in the study. The South region was the default in the model. The results suggest that the North East and Midwest regions have

more demand for crop insurance compared with the South. The demand for crop insurance is low in the West region. All the regional dummy variables are significant at the 5% level except the Midwest region. This result is in accordance with Figure 3 of the Glauber (2007) study which states that Midwest and Northern plains states tend to insure at high levels of coverage.

Figure 6.7: Estimates of regional variables on crop insurance participation



Weather Variables:

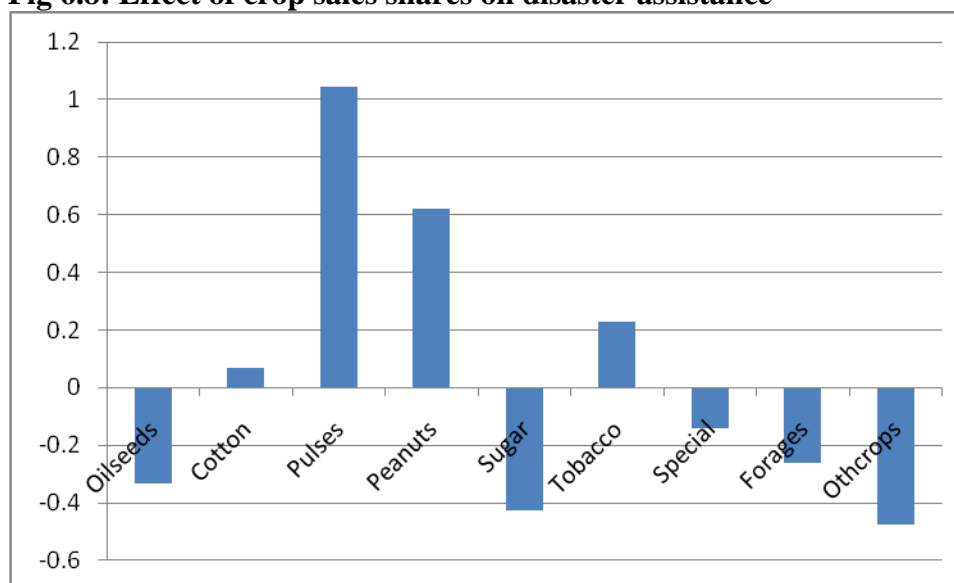
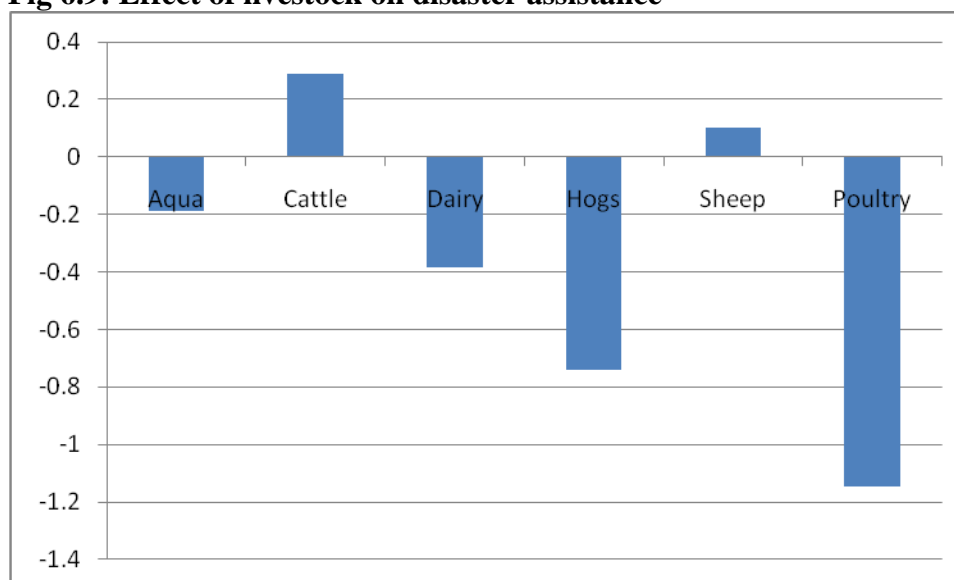
Long-run temperature is found to have a positive effect on crop insurance purchase, significant at 5% level. Long-run precipitation temperature is found to have a negative effect on crop insurance purchase, significant at 5% level. This suggests that crop insurance purchase is more likely in hotter,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

Disaster Assistance Analysis:

The estimated coefficients, standard errors and the significance of the variables are shown in Table 6.3. None of the age variables appeared to have a statistically significant impact on the probability of receiving disaster payments. Compared to the default category (some college/tech school) all the education category coefficients were negative and all except some high school were significant. The results do not suggest any clear, easy-to-interpret, relationships between age, education, and disaster payments.

Coefficients for the largest and smallest three sales classes were negative and significant. This suggests a type of inverted U-shaped relationship between farm sales and receipt of disaster payments. The results also suggest that farms reliant upon farming for their total household incomes are more likely to receive disaster payments. Farms in the middle categories for percent of farmland owned also appear to have higher probabilities of receiving disaster payments, again suggesting an inverted U relationship.

The farmers with significant share sales from pulses, peanuts, and cattle were more likely to receive disaster payments (i.e. had statistically significant, positive coefficients). Farmers with a larger share of sales in oilseeds, specialty crops, other crops, forage, dairy, poultry, and hogs were less likely to receive payments. The size of the coefficients is shown in the following graph:

Fig 6.8: Effect of crop sales shares on disaster assistance**Fig 6.9: Effect of livestock on disaster assistance**

The four dummy variables for committees overseeing disaster relief are included in the model. These are included to see if having a representative from your state on one of these committees increases your odds of receiving payments. The coefficient for the Senate agricultural sub-committee had a significant positive effect on disaster payments.

The other three sub-committees House, Senate appropriation and House agricultural sub-committees are not significant in the model. This result is consistent with the finding of Garrett et al. (2006) that political influence affects receipt of disaster payments.

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.

Regional Dummy variables suggest that South region (dropped from the model) receives higher disaster payments compared to other 3 regions (Midwest, Northeast and West). These variables are highly significant at 1% level.

The error correlation term (ρ) is 0.48. Rho is statistically significant at 1% level. This suggests that more efficient parameter estimates can indeed be obtained by using the bivariate probit specification.

Marginal Effects:

Table 6.4 and 6.5 report the marginal effects on the probabilities of crop insurance participation and disaster payments respectively for different significant explanatory variables.

The marginal effect of categorical variable depicts the change of independent variable compared to the dropped (default) variable in that category, and continuous variables are calculated at the sample means. For example, the marginal effect of change in edu_1 on probability of crop insurance=1 is computed as follows:

$\Pr(\text{crop insurance}=1 \mid \text{edu}_1=1) - \Pr(\text{crop insurance}=1 \mid \text{edu}_1=0)$, holding categorical variables at their mode and continuous variables at their sample means.

Among the age category group, producers with age greater than 65 years have the largest marginal impact. The probability of participation in crop insurance for farmers with age category of 65 years and above decreases by 20.4% compared to default 45-54 years age category. The marginal effect for lower education category (edu_1 – edu_3) has negative effect and higher education category (edu_5 – edu_6) has positive effect on crop insurance participation. The marginal effect of edu_5 (college bachelors degree) is estimated to increase the probability of crop insurance purchase by 17.3%. Farmers with lower income category (FarmY/TotalY_1 and FarmY/TotalY_2) have a high negative marginal effect on crop insurance participation with 53% compared to FarmY/totally_5 category. Percentage of own farm has a significant positive effect on crop insurance purchase. Farmers with 26-50% of own farm (ownfarm_3) are 32.5% more likely to buy crop insurance than 76-100% of own farm farmers.

Education has a significant negative effect on disaster payments with edu_1 category having a negative magnitude of 24.5%. Income variables FarmY/TotalY_1 and FarmY/TotalY_2 are estimated to decrease the probability of receipt of disaster payments by 46% and 48% respectively than FarmY/TotalY_5 category farmers. Farmers who had one of their senators on the Senate Agricultural Committee had a 28% greater probability of receiving disaster payments. For every 1% increase in the share of pulses increases the probability of receipt of disaster payments by 54.1%. The probability of receipt of disaster payments by northeast region decreases by 36.14% than south region. In the sample, the drought variable ranges from zero (for no drought conditions to extreme dry conditions (with a value of -3.0775). Moving from no-drought to the worst drought conditions increased the probability of receiving disaster payments decreases by 9.5%. The flood variable, in the sample takes on values from zero (neither wet nor dry conditions) to a maximum value of 4.8587. Increasing the flood variable to its minimum to maximum sample value increases the probability of receiving disaster payments by 4.7%. Finally, the results suggest that for every one-degree increase in temperature above the 30-year annual average, the probability of receiving disaster payments increases 5%.

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.

$$L.R = - 2 (\ln (\text{likelihood for restrictive model}) - \ln (\text{likelihood for full model}))$$

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 \neq 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

$$L.R = - 2 (\ln (\text{likelihood for restrictive model}) - \ln (\text{likelihood for full model}))$$

$$\text{L.R chi2 (10)} = 20.78$$

$$\text{Prob} > \text{chi2} = 0.0225$$

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

Education:

$$H_0 = \text{All Education variables} = 0$$

$$H_a = \text{All Education variables} \neq 0$$

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).

$$\text{LR for the full model} = -12915.21$$

$$\text{LR for the restrictive model} = -12958.76$$

$$\text{L.R} = -2 (\ln (\text{likelihood for Restrictive model}) - \ln (\text{likelihood for full model}))$$

$$\text{L.R chi2 (10)} = 87.1$$

$$\text{Prob} > \text{chi2} = 0.000$$

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

Sale Class:

$$H_0 = \text{All Sale Class variables} = 0$$

$$H_a = \text{All Sale Class variables} \neq 0$$

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 \neq 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:

$H_0 = \text{All Own farm variables} = 0$

$H_a = \text{All Own farm variables} \neq 0$

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

$L.R = -2 (\ln (\text{likelihood for Restrictive model}) - \ln (\text{likelihood for full model}))$

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		
		0	1
Predicted Values	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 =

$(\text{Correct number of predictions} - n) / (\text{Total number of observations} - n)$

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.

Table: 6.2: Factors affecting crop insurance participation**Dependent Variable: Crop Insurance**

Variable	Estimate	Std. Error	p-value
Agele25	-0.1734	(0.3110)	0.5770
Age25_34	0.0167	(0.0706)	0.8120
Age35_44	-0.0313	(0.0416)	0.4520
Age55_64	-0.0331	(0.0334)	0.3200
Agegt65	-0.1380***	(0.0382)	0.0000
Edu_1	-0.3152***	(0.1068)	0.0030
Edu_2	-0.2463***	(0.0840)	0.0030
Edu_3	-0.0864**	(0.0341)	0.0110
Edu_5	0.1608***	(0.0340)	0.0000
Edu_6	0.0900*	(0.0502)	0.0730
SaleClass_1	-1.1403***	(0.0674)	0.0000
SaleClass_2	-0.5106***	(0.0430)	0.0000
SaleClass_3	-0.2012***	(0.0393)	0.0000
SaleClass_5	0.0903**	(0.0413)	0.0290
SaleClass_6	0.0805	(0.0530)	0.1290
SaleClass_7	-0.0476	(0.0658)	0.4690
Farm Y/Total Y_1	-0.3846***	(0.0947)	0.0000
Farm Y/Total Y_2	-0.3293***	(0.0477)	0.0000
Farm Y/Total Y_3	-0.0558	(0.0407)	0.1710
Farm Y/Total Y_4	-0.0128	(0.0376)	0.7330
%Ownfarm_1	0.1112**	(0.0559)	0.0470
%Ownfarm_2	0.2552***	(0.0412)	0.0000
%Ownfarm_3	0.3191***	(0.0390)	0.0000
%Ownfarm_4	0.2795***	(0.0394)	0.0000
Oilseeds	0.0657	(0.0977)	0.5010
Cotton	-0.1373	(0.1178)	0.2440
Pulses	0.3974	(0.3249)	0.2210
Peanuts	0.5475*	(0.3249)	0.0920
Sugar	0.0795	(0.3252)	0.8070
Tobacco	-0.1945	(0.2238)	0.3850
Special	-0.7225***	(0.0605)	0.0000
Forages	-0.5386***	(0.0890)	0.0000

Othcrops	-0.8860***	(0.1060)	0.0000
Aqua	-0.8218***	(0.2254)	0.0000
Cattle	-0.4806***	(0.0484)	0.0000
Dairy	-0.7537***	(0.0612)	0.0000
Hogs	-0.4584***	(0.1193)	0.0000
Sheep	-0.6181***	(0.1552)	0.0000
Poultry	-1.2597***	(0.1377)	0.0000
Premium	-0.0029	(0.0128)	0.8160
Diversification	0.0333	(0.1217)	0.7840
Int_prem_diverse	0.0038	(0.0156)	0.8050
Longruntemp	0.0075**	(0.0038)	0.0440
Longrunppt	-0.1989***	(0.0214)	0.0000
Dum_midwest	0.0964	(0.0646)	0.1350
Dum_northeast	0.1604**	(0.0792)	0.0430
Dum_west	-0.1873**	(0.0738)	0.0110
Constant	0.0642	(0.2442)	0.7930
<hr/>			
*** Significant at 1%	** Significant at 5%	* Significant at 10%	

Table: 6.3: Factors affecting disaster payments**Dependent Variable: Disaster Assistance**

Variable	Estimate	Std. Error	p-value
Agele25	-0.3323	(0.3054)	0.2770
Age25_34	0.0456	(0.0670)	0.4960
Age35_44	0.0476	(0.0399)	0.2320
Age55_64	-0.0338	(0.0318)	0.2870
Agegt65	-0.0523	(0.0351)	0.1360
Edu_1	-0.3380***	(0.0973)	0.0010
Edu_2	-0.0660	(0.0736)	0.3700
Edu_3	-0.0527*	(0.0317)	0.0960
Edu_5	-0.0681**	(0.0327)	0.0380
Edu_6	-0.0792*	(0.0472)	0.0940
SaleClass_1	-0.8325****	(0.0551)	0.0000
SaleClass_2	-0.2354****	(0.0406)	0.0000
SaleClass_3	-0.0880**	(0.0383)	0.0220
SaleClass_5	-0.0038	(0.0409)	0.9240
SaleClass_6	-0.0476	(0.0531)	0.3700
SaleClass_7	-0.2721****	(0.0661)	0.0000
Farm Y/Total Y_1	-0.4840****	(0.0780)	0.0000
Farm Y/Total Y_2	-0.4466****	(0.0438)	0.0000
Farm Y/Total Y_3	-0.1788****	(0.0393)	0.0000
Farm Y/Total Y_4	-0.0201	(0.0364)	0.5810
%Ownfarm_1	0.0245	(0.0521)	0.6380
%Ownfarm_2	0.2082****	(0.0395)	0.0000
%Ownfarm_3	0.1802****	(0.0382)	0.0000
%Ownfarm_4	0.2303****	(0.0376)	0.0000
Oilseeds	-0.3341****	(0.1025)	0.0010
Cotton	0.0680	(0.1113)	0.5410
Pulses	1.0459****	(0.3297)	0.0020
Peanuts	0.61978**	(0.2991)	0.0380
Sugar	-0.4269	(0.3241)	0.1880
Tobacco	0.2271	(0.1896)	0.2310
Special	-0.1413**	(0.0568)	0.0130
Forages	-0.2614****	(0.0821)	0.0010

Othcrops	-0.4738***	(0.0895)	0.0000
Aqua	-0.1869	(0.1867)	0.3170
Cattle	0.2871***	(0.0458)	0.0000
Dairy	-0.3832***	(0.0621)	0.0000
Hogs	-0.7412***	(0.1291)	0.0000
Sheep	0.1024	(0.1180)	0.3850
Poultry	-1.1480***	(0.1373)	0.0000
Diversification	0.0406	(0.0522)	0.4360
Dum_hagcom	0.0609	(0.0378)	0.1070
Dum_hapcom	-0.0056	(0.0325)	0.8620
Dum_sagcom	0.2806***	(0.0421)	0.0000
Dum_sapcom	0.0022	(0.0292)	0.9400
Drought	-0.0625***	(0.0211)	0.0030
Flood	0.0557***	(0.0142)	0.0000
Longruntemp	-0.0033	(0.0039)	0.4050
Longrunppt	-0.0186	(0.0278)	0.5050
Diff_temp	0.3142***	(0.0489)	0.0000
Dum_midwest	-0.5022***	(0.0707)	0.0000
Dum_northeast	-0.5685***	(0.0883)	0.0000
Dum_west	-0.3236***	(0.0708)	0.0000
Constant	-0.0670	(0.2471)	0.7860
Rho	0.4821***	(0.0183)	0.0000

*** Significant at 1%

** Significant at 5%

* Significant at 10%

Table6.4: Marginal effects of factors affecting crop insurance participation

The marginal predicted probabilities where crop insurance takes the value of 1.

Variable	Marginal Effect
Agegt65	-0.2044
Edu_1	-0.2732
Edu_2	-0.2780
Edu_3	-0.0416
Edu_5	0.1727
Edu_6	0.1568
SaleClass_1	-0.8350
SaleClass_2	-0.2676
SaleClass_3	-0.0787
SaleClass_5	0.3514
Farm Y/Total Y_1	-0.5300
Farm Y/Total Y_2	-0.5330
%Ownfarm_1	0.0225
%Ownfarm_2	0.3152
%Ownfarm_3	0.3247
%Ownfarm_4	0.2387
Peanuts	0.2776
Special	-0.2006
Forages	-0.2836
Othcrops	-0.3172
Aqua	-0.2121
Cattle	-0.1611
Dairy	-0.0912
Hogs	-0.0324
Sheep	-0.3464
Poultry	-0.3215
Longruntemp	0.0004
Longrunppt	-0.0648
Dum_northeast	0.2537
Dum_west	-0.0587

Table6.5: Marginal effects of factors affecting disaster payments

The marginal predicted probabilities where Disaster Assistance takes the value of 1.

Variable	Marginal Effect
Edu_1	-0.2454
Edu_3	-0.0011
Edu_5	-0.0406
Edu_6	-0.1628
SaleClass_1	-0.6759
SaleClass_2	-0.0634
SaleClass_3	-0.1515
SaleClass_7	-0.0426
Farm Y/Total Y_1	-0.4674
Farm Y/Total Y_2	-0.4812
Farm Y/Total Y_3	-0.0274
%Ownfarm_2	0.2434
%Ownfarm_3	0.2020
%Ownfarm_4	0.2472
Oilseeds	-0.0243
Pulses	0.5410
Peanuts	0.3528
Special	-0.0923
Forages	-0.2192
Othcrops	-0.2424
Cattle	0.0445
Dairy	-0.0208
Hogs	-0.1831
Poultry	-0.2972
Dum_sagcom	0.2807
Drought	-0.0954
Flood	0.0472
Diff_temp	0.0562
Dum_midwest	-0.0898
Dum_northeast	-0.3614
Dum_west	-0.0801

References

Anderson, J.D, B.J. Barnett, and K.H. Coble. "Impacts of a Standing Disaster Payment Program on U.S. Crop Insurance." Paper prepared for presentation at the 108th EAAE Seminar 'Income stabilisation in a changing agricultural world: policy and tools', Warsaw, February 8-9, 2008.

Aradhyula, S., and R. Tronstad. "Does Tourism Promote Cross-Border Trade?." *American Journal Of Agricultural Economics* 85, 569-579, 2003.

Barnett, B.J., and J.R. Skees. "An Empirical Analysis of the Demand for Multiple Peril Crop Insurance: Comment." *American Journal Of Agricultural Economics* 76, 948-951, 1994.

Barnett, B.J., S.R. Skees, and J.D. Hourigan. "Examining Participation in Federal Crop Insurance." Staff paper #275, Department of Agricultural Economics, University of Kentucky, August 1990

Barry, P.J., P.N. Ellinger, G.D. Schnitkey, B.J. Sherrick, and B.C. Wansink. "The Crop Insurance Market: Producer Preferences and Product Attributes". Study conducted under a cooperative agreement with the Economic Research Service of the U.S. Department of Agriculture, 2002.

Black, D.L., and J.H. Dorfman. "Identifying Farmer Characteristics Related to Crop Insurance Purchase Decisions." Paper presented at AAEA Annual Meeting, Tampa, Florida, 2000.

Changnon, S.A. "Impacts of the Midwestern Drought Forecasts of 2000". *Journal of Applied Meteorology* 41, 1042-1052, 2002.

Coble, K.H., T.O.Knight, R.D.Pope, and J.R.Williams. "Modeling Farm-Level Crop Insurance Demand with Panel Data." *American Journal Of Agricultural Economics* 78, 439-437, 1996.

Duncan, J., and R.J. Myers. "Crop Insurance under Catastrophic Risk." *American Journal Of Agricultural Economics* 82, 842-855, 2000.

Garrett. T.A., T.L. Marsh, M.I. Marshall. "Political allocation of US agriculture disaster payments in the 1990s." *International Review of Law and Economics* 26, 143-161, 2006.

Glauber, J.W. "Crop Insurance Reconsidered." *American Journal Of Agricultural Economics* 86, 1179-1195, 2004.

Glauber, J.W. "Double Indemnity: Crop Insurance and the Failure of U.S. Agricultural Disaster Policy." Paper prepared for American Enterprise Institute project, Agricultural Policy for the 2007 Farm Bill and Beyond, 2007.

Goodwin, B.K. "An Empirical Analysis Of The Demand For Multiple Peril Crop Insurance." *American Journal Of Agricultural Economics* 75, 425-434, 1993.

Goodwin, B.K., and R.M. Rejesus. "Safety Nets or Trampolines? Federal Crop Insurance, Disaster Assistance, and the Farm Bill." *Journal of Agricultural and Applied Economics* 40, 415-429, 2008.

Knight, T.O., and K.H. Coble. "A Survey of Multiple Peril Crop Insurance Literature Since 1980." *Review of Agricultural Economics* 19, 128-156, 1997.

Luo, H., J.R. Skees and M.A. Marchant. "Weather Information and the Potential for Intertemporal Adverse Selection in Crop Insurance." *Review of Agricultural Economics* 16, 441-451, 1994.

Sherrick, B.J., P.J. Barry, P.N. Ellinger and G.D. Schnitkey. "Factors Influencing Farmers' Crop Insurance Decisions." *American Journal Of Agricultural Economics* 86, 103-114, 2004.

Skees, J.R., and M.R. Reed. "Rate Making for Farm-Level Crop Insurance: Implications for Adverse Selection." *American Journal Of Agricultural Economics* 68, 653-659, 1986.

Smith, V.H., and A. Baquet. "The Demand for Multiple Peril Crop Insurance: Evidence from Montana Wheat Farms." *American Journal Of Agricultural Economics* 78, 189-201, 1996.

Smith, V.H., and B.K. Goodwin. "Crop Insurance, Moral Hazard, and Agricultural Chemical Use." *American Journal Of Agricultural Economics* 78, 428-438, 1996.

APPENDIX

Basic Definitions:

Crop Insurance:

Crop Insurance is generally purchased by the farmers, ranchers to protect themselves against the loss of crop against natural calamities like drought, flood, hail or the loss of revenue due to decline in the prices of agricultural commodities.

(Source: http://en.wikipedia.org/wiki/Crop_insurance)

Crop Insurance is classified in to two categories namely Crop-yield Insurance and Crop-revenue insurance.

- 1) Crop-yield Insurance: The crop insurance that pays indemnities to farmers based on yield losses due to natural causes. Crop-yield insurance is classified in to two main classes.
 - a) Crop-hail Insurance: Hail is a narrow peril that occurs in a limited place and is generally available from private insurers only.
 - b) Multiple Peril Crop Insurance (MPCI): This insurance provides comprehensive protection against the perils of drought, floods, insects, disease etc which may affects many insured at the same time and present the insurer with excessive losses. All the above perils are combined together in a single policy called MPCI.
- 2) Crop-revenue Insurance: It is the combination of both crop-yield insurance and price insurance. This plan is offered to farmers that pay indemnities based on revenue shortfalls. This insurance is subsidized by Risk Management Agency.

Catastrophic Risk Protection (CAT):

For the crop losses of 50 percent of the APH yield and above Risk Management Agency (RMA) indemnifies 55 percent of market price of commodity under CAT. Producers must pay a \$ 100 administrative fee for each crop insured in each county. This is the minimum level of coverage required offered by FCIC for a person to qualify for other USDA program benefits. The Federal Government pays the premium on coverage.

(Source: <http://agmarketing.extension.psu.edu/Business/CropInsurance.html>)

Buy-up Coverage:

This coverage covers the insured crop above the catastrophic coverage (CAT) level. This coverage is available up to 85% of expected yield or expected revenue.

Insured Crop:

The crop in the county for which coverage is available under the policy as shown on the application accepted by the insurance company.

(Source: http://agecoext.tamu.edu/fileadmin/user_upload/Documents/Resources/Risk_Management/rm4-11.pdf)

Premium:

A premium is the dollar cost per acre of the insurance policy. The farmer pays the premium to the insurance company for coverage.

(Source:

http://www.cropinsurance.org/educational_projects/crop_insurance_glossary.pdf)

Subsidies

A subsidy is a grant of money by the federal government made to farm businesses in order to promote commercial enterprise or to protect the delivery system of food and fiber to the general economy.

(Source:

http://www.cropinsurance.org/educational_projects/crop_insurance_glossary.pdf)

Variable Definitions:

<u>Variable</u>	<u>Description</u>
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 ranch	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 $\min[\text{PHDI}, 0]$
FLOOD Hydrological	Captures deviation from normal annual average of Palmers Drought Index (PHDI) for year 2005. Calculated as $\max[\text{PHDI}, 0]$
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 (109 th Congress), 0 otherwise
DUM_HAPCOM representative	Dummy variable which is equal to one if the state has a

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