



**AgEcon** SEARCH  
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

*The World's Largest Open Access Agricultural & Applied Economics Digital Library*

**This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.**

**Help ensure our sustainability.**

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

[aesearch@umn.edu](mailto:aesearch@umn.edu)

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

**Does Crop Insurance Really Reassure Farmers? A Puzzle and its Explanations Based on  
Field Data**

**Juan He**  
School of Economics and Management  
Huazhong Agricultural University  
[hejuan@mail.hzau.edu.cn](mailto:hejuan@mail.hzau.edu.cn)

**Xiaoyong Zheng**  
Department of Agricultural and Resource Economics  
North Carolina State University  
[xzheng@ncsu.edu](mailto:xzheng@ncsu.edu)

*Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics  
Association Annual Meeting, Chicago, Illinois, July 30-August 1*

*Copyright 2017 by Juan He, Xiaoyong Zheng. All rights reserved. Readers may make  
verbatim copies of this document for non-commercial purposes by any means, provided that  
this copyright notice appears on all such copies.*

# Does Crop Insurance Really Reassure Farmers? A Puzzle and its Explanations Based on Field Data

## **Abstract**

We find a puzzling situation that risk-averse farmers have lower demand for crop insurance in the Philippines corn insurance market, and thus, provide possible reasons based on theoretical models and empirical evidence. In the theoretical framework, different from other insurance models with basis risk, we adopt a convenient way of representing agents' risk averseness, so an explicit condition can be derived for the relationship between risk averseness and insurance demand. Then, the implication of insurance models with basis risk is tested using survey data collected from corn producers in the Philippines. We find that farmers make insurance purchase decisions based on the perceived basis risk not the actual one. The implications of this finding are also discussed.

## **Introduction**

According to classical insurance models, as farmers become more risk averse and are willing to pay higher risk premium, they are more likely to participate into insurance programs. However, empirical evidence does not always support such a predication. For example, Giné Townsend, and Vickery (2007) show that in rural India, risk-averse farmers demand less rainfall insurance. Since other empirical studies point out that lacking of trust plays a role in insurance participation (e.g. Cai, et al., 2014, and Cole, et al., 2013), Giné Townsend, and Vickery (2007) speculate that risk-averse farmers tend to place less trust in the index insurance product, so they are less likely to purchase it.

To dig into other reasons behind this puzzle, Clark (2016) develops a model of index insurance with basis risk and show that when considering the existence of basis risk, the relationship between risk averseness and insurance demand is non-monotonic. Basis risk is originally referred to the risk of contractual non-performance in derivative markets, and here it is extended to refer to the risk that is not covered by

insurance. For example, a farmer with rainfall insurance may not get any indemnity when a localized weather event hits. In this scenario, the farmer loses his insurance premium as well as carries the loss from the risk event, so the most risk averse farmers find this type of insurance unattractive. Therefore, basis risk can be used to explain the low demand among risk averse farmers for index insurance.

As for the indemnity insurance, though no previous research has shown the same empirical puzzle as in index insurance, Doherty and Schlesinger (1990) construct an insurance model in which insurance contract may be nonperforming. Specifically, insurance may fail to perform due to insurers' insolvency, agents' being uncertainty that a claim may be rendered invalid by the court, payments' being delayed, or the uncontrollable conditions that are stipulated in insurance contracts. Within this analysis framework, it can be shown that the non-monotonic relationship between risk averseness and insurance demand also exists. Though this type of models with "basis risk" can be used to explain the puzzle of negative relationship between risk averseness and insurance demand, these models do not provide a definite condition on which risk averseness is positively or negatively correlated with insurance demand.

In this research, we present another piece of this type of empirical puzzle, showing low demand among risk averse farmers can also be found for indemnity insurance. Using a survey dataset on 426 farmers from the Philippines, we first use a Probit model to examine the factors influencing farmers' real demand for crop insurance and show the evidence that risk-averse farmers are less likely to demand insurance. Then, since there are two types of insurances with different basis risk levels, we use two Probit models as well as an ordered Logit model to find the variables that influence farmers' decisions on selecting between insurance types and test the predication from insurance models with basis risk that as basis risk diminishes, risk-averse farmers find insurance more attractive. However, the results suggest that the farmers who are more risk-tolerant still tend to purchase the insurance type with little basis risk. Therefore, it implies farmers make their decisions based on the perceived basis risk rather than the real one.

Our contribution in this analysis is twofold. First, we develop a model in which a

definite condition for the positive or negative relationship between risk averseness and insurance demand can be derived. As Ross (1981) points out that Arrow-Pratt measure of risk aversion (Pratt, 1964) is too weak and may give ambiguous results for problems, we adopt a convenient way of describing risk averseness and derive the explicit condition. Second, we test the implication from those insurance models with basis risk and show that farmers make their decisions based on the perceived basis risk rather than the real one. Hence, the result incorporates both the “lacking of trust” and “basis risk” stories suggested by other researchers in solving the puzzle of low insurance demand among risk averse farmers, because “lacking of trust” can be modeled as higher perceived basis risk.

Nowadays, crop insurance programs have become a crucial measure of improving farmers’ welfare. Therefore, finding ways to boost insurance participation becomes a pressing need. Using the framework and evidence provided by this research, we can understand more about the real world situation behind insurance demand and find more efficient approaches to improve insurance programs, such as building farmers’ trust in crop insurance, or designing insurance products minimizing perceived or actual basis risk.

The rest of the paper is organized as follows. The next Section describes the theoretical framework in which conditions for the relationship between risk averseness and insurance demand are derived. Sections three and four introduce the Philippine crop insurance program and our data, respectively. Our empirical strategy is detailed in Section five. Section six reports and discusses the results. The final Section concludes.

### **Conceptual Framework: Basis Risk in Crop Insurance**

To illustrate basis risk within a crop insurance context, we develop a simple theoretical model that incorporates a convenient risk averseness measure proposed by De Meza and Webb (2001). This risk averseness measure uses units of pseudo wealth ( $\alpha$ ) to represent the level of risk aversion. Specifically, we assume that there are two types of producers, one “bold” and the other one “cautious.” The utility functions for

the two types of farmers are defined as follows:

$$U_B(w) = U(\alpha + w);$$

$$U_C(w) = U(w),$$

where  $B$  denotes bold,  $C$  denotes cautious,  $w$  is the wealth level, and  $U$  is a utility function with  $U' > 0$ ,  $U'' < 0$ , and  $-\frac{U''}{U'}$  is constructed for decreasing absolute risk-aversion (DARA). The bold type behaves as if they had  $\alpha$  units more wealth than the cautious type. Therefore, with the same wealth  $w$ , bold farmers are less risk-averse than cautious farmers. For each farmer, with probability  $p_i$ , there will be no loss during production. With probability  $1 - p_i$ , there will be a loss of  $L$ . The no-loss probability  $p_i$  is different for different farmers and is assumed to be randomly distributed across farmers according to a uniform distribution on  $[0, 1]$ . Each farmer knows his own  $p_i$  when he makes the decision on whether to purchase crop insurance. If he purchases insurance that covers this type of loss and loss occurs, then he will receive an indemnity payment of  $L$ .

The crop insurance in the Philippines, however, as we explain in detail in the next section, offers partial coverage and full coverage, that is, the natural disaster only cover and the multi-risk cover. For example, if a farmer purchases the natural disaster only cover and there is a loss due to pests, the farmer will not receive any indemnity payments from the insurance company. This means that the farmer could actually be worse off than if he had not purchased insurance. The literature on agricultural index insurance has discussed this point quite extensively (e.g. Clarke, 2016; Carter, Cheng and Sarris, 2016) and shown that allowing this possibility can lead to quite different conclusions than models that do not allow this possibility. Therefore, it is interesting to examine the relationship between risk averseness and insurance demand when this possibility (i.e., partial coverage) is considered in our context.

Formally, assume the expected utility for the representative farmer  $i$  when he does not purchase insurance is the same as before, that is,

$$EU_i(w_0) = p_i U(w_0) + (1 - p_i) U(w_0 - L).$$

On the other hand, his expected utility when he purchases insurance is,

$$EU_i(w_0) = p_i U(w_0 - y) + (1 - p_i)[\gamma U(w_0 - y) + (1 - \gamma)U(w_0 - y - L)],$$

where  $1 - \gamma$  ( $0 < \gamma \leq 1$ ) is the basis risk and represents the probability that the loss is due to a cause not covered by the insurance purchased. There is a threshold  $\bar{p}$ , at which this farmer is indifferent between no insurance and natural disaster only cover. The threshold no-loss probability  $\bar{p}$  such that the farmer is indifferent between participating in the crop insurance program and not participating must satisfy the following equation,

$$\frac{\bar{p}}{1-\bar{p}} = \frac{\gamma U(w_0-y) + (1-\gamma)U(w_0-y-L) - U(w_0-L)}{U(w_0) - U(w_0-y)}. \quad (4)$$

We are now ready to state the following theorem.

**THEOREM (“U” SHAPED RELATIONSHIP BETWEEN RISK AVERSENESS AND INSURANCE PARTICIPATION):** The threshold no-loss probability for the cautious type is higher than that of the bolder type, that is  $\bar{p}_C > \bar{p}_B$ , when  $\gamma > \gamma^*$  where:

$$\gamma^* = 1 - \frac{\left\{ \begin{array}{l} [U'(\alpha+w-y) - U'(\alpha+w-L)][U(\alpha+w) - U(\alpha+w-y)] \\ - [U(\alpha+w-y) - U(\alpha+w-L)][U'(\alpha+w) - U'(\alpha+w-y)] \end{array} \right\}}{\left\{ \begin{array}{l} [U'(\alpha+w-y) - U'(\alpha+w-y-L)][U(\alpha+w) - U(\alpha+w-y)] \\ - [U(\alpha+w-y) - U(\alpha+w-y-L)][U'(\alpha+w) - U'(\alpha+w-y)] \end{array} \right\}}$$

**PROOF:** It can be seen from (4) that there is a threshold  $\bar{\gamma}_1$  such that when  $\gamma < \bar{\gamma}_1$ , the numerator of the right hand side (RHS) of (4) is negative, and no such  $\bar{p}$  exists. Under this condition, that is, when the basis risk is quite large, farmers are always better off without insurance.  $\bar{\gamma}_1$  is defined implicitly by the following equation,

$$\bar{\gamma}_1 U(\alpha + w - y) + (1 - \bar{\gamma}_1)U(\alpha + w - y - L) = U(\alpha + w - L).$$

Therefore, the participation threshold  $\bar{p}$  exists only when the basis risk is low enough such that  $\gamma \geq \bar{\gamma}_1$ . Below we focus on the case where  $\gamma \geq \bar{\gamma}_1$ .

Next, we consider the effect of  $\alpha$  on the participation decision. Recall  $\alpha$  describes the farmer’s degree of boldness. The larger  $\alpha$  is, the bolder the farmer is. Taking the derivative of (4) with respect to  $\alpha$  yields the following equation,

$$\frac{\partial \frac{\bar{p}}{1-\bar{p}}}{\partial \alpha} = \frac{[\gamma U'(\alpha+w-y) + (1-\gamma)U'(\alpha+w-y-L) - U'(\alpha+w-L)]}{* [U(\alpha+w) - U(\alpha+w-y)] - A} \quad (5)$$

where  $A = [\gamma U(\alpha + w - y) + (1 - \gamma)U(\alpha + w - y - L) - U(\alpha + w - L)][U'(\alpha + w) - U'(\alpha + w - y)]$  and  $B = [U(\alpha + w) - U(\alpha + w - y)]^2$ . Since  $\gamma \geq \bar{\gamma}_1$  and

$U'' < 0$ , we have  $A \leq 0$  and  $B > 0$ . Let  $\bar{\gamma}_2$  be the  $\gamma$  that satisfies the following equation,

$$\bar{\gamma}_2 U'(\alpha + w - y) + (1 - \bar{\gamma}_2) U'(\alpha + w - y - L) = U'(\alpha + w - L).$$

Then, when  $\gamma > \bar{\gamma}_2$ , the numerator of the RHS of (5) can either be negative or positive and as a result,  $\frac{\partial \bar{p}}{\partial \alpha}$  can either be positive or negative. On the other hand, when  $\gamma \leq \bar{\gamma}_2$ ,  $\frac{\partial \bar{p}}{\partial \alpha}$  is non-negative for sure. However, as Corollary below shows,  $\frac{\partial \bar{p}}{\partial \alpha}$  is decreasing in  $\gamma$  and  $\frac{\partial \bar{p}}{\partial \alpha} |_{\gamma=1} < 0$ . Therefore,  $\frac{\partial \bar{p}}{\partial \alpha} < 0$  when  $\gamma$  is large enough. The  $\gamma^*$  that makes  $\frac{\partial \bar{p}}{\partial \alpha} = 0$  can be further calculated as

$$\gamma^* = 1 - \frac{\frac{\partial \bar{p}}{\partial \alpha} |_{\gamma=1}}{\frac{\partial^2 \bar{p}}{\partial \alpha \partial \gamma}} = 1 - \frac{\left\{ \begin{array}{l} [U'(\alpha+w-y) - U'(\alpha+w-L)][U(\alpha+w) - U(\alpha+w-y)] \\ - [U(\alpha+w-y) - U(\alpha+w-L)][U'(\alpha+w) - U'(\alpha+w-y)] \end{array} \right\}}{\left\{ \begin{array}{l} [U'(\alpha+w-y) - U'(\alpha+w-y-L)][U(\alpha+w) - U(\alpha+w-y)] \\ - [U(\alpha+w-y) - U(\alpha+w-y-L)][U'(\alpha+w) - U'(\alpha+w-y)] \end{array} \right\}}.$$

Therefore, when  $\gamma > \gamma^*$ ,  $\frac{\partial \bar{p}}{\partial \alpha}$  is negative and we have  $\bar{p}_C > \bar{p}_B$ . This completes the proof.

**REMARK:** When  $\bar{\gamma}_1 \leq \gamma \leq \bar{\gamma}_2$ , the numerator of the RHS of (5) is positive and as a result,  $\bar{p}_C < \bar{p}_B$ . In this case, the more cautious farmers are less likely to purchase insurance. It is similar to the situation modeled by Clarke (2016), where the more cautious (or the more risk averse) farmers have less demand for insurance. When  $\bar{\gamma}_1 \leq \bar{\gamma}_2 < \gamma$  or  $\bar{\gamma}_2 \leq \bar{\gamma}_1 < \gamma$ , as we show above, the relationship between boldness and participation is first positive and then becomes negative as  $\gamma$  increases. When the basis risk  $(1 - \gamma)$  is low enough such that  $\gamma > \gamma^*$ , we have the result that cautious farmers are more likely to purchase insurance, with is consistent with the classic insurance models. This non-linear relationship between boldness and participation is similar to the hump-shaped relationship between coverage and risk-averseness as illustrated by the simulation results in Clarke (2016) for index insurance.

**Corollary (BASIS RISK EFFECT ON ATTRACTIVENESS OF INSURANCE):**

The expression  $\frac{\partial \bar{p}}{\partial \alpha}$  is decreasing in  $\gamma$  and  $\frac{\partial \bar{p}}{\partial \alpha} |_{\gamma=1} < 0$ .

**PROOF:** Taking the derivative of  $\frac{\partial \bar{p}}{\partial \alpha}$  in (5) with respect to  $\gamma$  yields,



$$\frac{\partial^2 \bar{p}}{\partial \alpha \partial \gamma} = \frac{1}{B} \{ [U'(\alpha + w - y) - U'(\alpha + w - y - L)] [U(\alpha + w) - U(\alpha + w - y)] - [U(\alpha + w - y) - U(\alpha + w - y - L)] [U'(\alpha + w) - U'(\alpha + w - y)] \}.$$

As a result,  $\frac{\partial^2 \bar{p}}{\partial \alpha \partial \gamma} < 0$  is equivalent to:

$$\frac{U'(\alpha + w - y) - U'(\alpha + w - y - L)}{U(\alpha + w - y) - U(\alpha + w - y - L)} < \frac{U'(\alpha + w) - U'(\alpha + w - y)}{U(\alpha + w) - U(\alpha + w - y)}. \quad (6)$$

When  $y$  is small compared to  $\alpha + w$ , the RHS of (6) can be written as  $\frac{U''(\alpha + w - y)}{U'(\alpha + w - y)}$ .

Therefore, (6) can be rewritten as

$$\frac{U'(\alpha + w - y) - U'(\alpha + w - y - L)}{U(\alpha + w - y) - U(\alpha + w - y - L)} < \frac{U''(\alpha + w - y)}{U'(\alpha + w - y)}. \quad (7)$$

(7) is equivalent to the inequality (2) in He (2016) with  $w$  replaced by  $\alpha + w - y$ .

Hence, we proved  $\frac{\partial \bar{p}}{\partial \alpha}$  is decreasing in  $\gamma$ .

Furthermore,

$$\frac{\partial \bar{p}}{\partial \alpha} \Big|_{\gamma=1} = \frac{1}{B} \{ [U'(\alpha + w - y) - U'(\alpha + w - L)] [U(\alpha + w) - U(\alpha + w - y)] - [U(\alpha + w - y) - U(\alpha + w - L)] [U'(\alpha + w) - U'(\alpha + w - y)] \}.$$

Therefore,  $\frac{\partial \bar{p}}{\partial \alpha} \Big|_{\gamma=1} < 0$  is equivalent to  $\frac{U'(\alpha + w - y) - U'(\alpha + w - L)}{U(\alpha + w - y) - U(\alpha + w - L)} < \frac{U'(\alpha + w) - U'(\alpha + w - y)}{U(\alpha + w) - U(\alpha + w - y)}$ ,

which is (6) above with  $L$  replaced by  $L - y$ . Hence, we proved  $\frac{\partial \bar{p}}{\partial \alpha} \Big|_{\gamma=1} < 0$ .

**REMARK:** The discussion and proof for Corollary above indicates that as basis risk  $(1 - \gamma)$  becomes smaller, cautious farmers find the crop insurance coverage increasingly attractive.

### **Empirical Background: The Philippine Crop Insurance Program**

In the Philippines, the agricultural industry has been recognized by the government as a key component to the country's economic development. Agriculture not only provides food and raw materials to other sectors, but also provides employment and absorbs a large portion of the working poor. However, high poverty rates are still prevalent in many agricultural subsectors (Reyes et al., 2015). Three out of every four poor individuals in the Philippines came from agricultural households (Reyes, Gloria and Mina, 2015).

According to the Rural Poverty Report (2011) of the International Fund for

Agricultural Development (IFAD), adverse weather shock is the major factor that contributes to impoverishment in the Philippines. Farmers could mitigate the impact of adverse weather shocks in several ways. They can adopt on-farm strategies to alleviate production risks, or purchase crop insurance, which is a recognized institutional tool to address shocks in agricultural production. Crop insurance is especially beneficial when farmers have been confronted with recent challenges imposed by climate change. The Philippines has a tropical maritime climate and it is more prone to natural disasters, such as floods and typhoons. As a result, this country is particularly vulnerable under climate change. One adverse weather event can instantly cause severe losses and poor farmers are usually unable to recover from these losses (Reyes et al., 2015). These situations give rise to the main theme of crop insurance programs in the Philippines, which is to make sure that farmers are able to restart production and rebuild their livelihood after severe losses.

#### *The Philippine Crop Insurance Corporation (PCIC)*

The crop insurance program in the Philippines is administered by the PCIC, a government-owned corporation. PCIC is mandated to provide insurance protection to agricultural producers against natural calamities, such as typhoons, floods, droughts, and earthquakes, as well as pests and diseases. It also provides insurance against loss of non-crop agricultural assets including machinery and equipment.

Different from crop insurance in other countries, crop insurance in the Philippines is regarded as both a risk management tool for farmers and a credit risk reduction mechanism for lending institutions. Crop insurance can be used as surrogate collateral when financial assistance is provided to agricultural producers, and farmers are required to purchase crop insurance when participating in government-sponsored credit programs. Crop insurance is viewed as a mechanism that provides incentives for lending institutions to make loans available to producers, especially in underdeveloped rural areas (Reyes et al., 2015).

### *The PCIC Corn Insurance Program*

Corn is one of the two major crops in the Philippines being insured by PCIC (the other one being rice).<sup>1</sup> In particular, there are two types of corn insurance offered by PCIC: (1) the natural disaster type, and (2) the multi-risk type. The natural disaster type only insures farmers against crop loss caused by natural disasters, such as typhoon, flood, drought and other natural calamities. The multi-risk type, on the other hand, covers a more comprehensive set of risks that includes all disasters covered under the natural disaster program, plus losses from pest infestation and plant diseases.

PCIC also classifies corn producers who buy coverage into two categories: (a) the borrower client, and (b) the self-financed client. The borrower client secures a production loan from a formal lending institution, and also purchases crop insurance. As mentioned above, formal government-sponsored lending institutions typically require purchase of crop insurance for farmers wanting to acquire loans from this source. The self-financed client, however, does not have loans from formal sources and only purchases crop insurance from PCIC.<sup>2</sup>

The insurance coverage (i.e., the liability amount) for corn is primarily determined based on the total cost of production inputs, as indicated in the Farm Plan and Budget that the farmers are required to submit upon application. The farmer also has the option to include an additional cover amount of up to 20% of the value of the expected yield, with the approval of the PCIC. As for its price, Reyes et al. (2015) point out that premium rates for corn insurance in the Philippines are largely based on historical data on damage rates (i.e., the ratio of indemnity to liabilities, which is also called the loss cost ratio) at the provincial level. Premium rates for the corn insurance product vary depending on: geographical location (i.e., different rates for different provinces), the type of insurance cover (natural disaster vs. multi-risk), and cropping

---

<sup>1</sup> The PCIC has seven major insurance product lines: rice, corn, high-value commercial crops (i.e., vegetables and fruits), livestock, fishery, non-crop agricultural asset, and term insurance packages.

<sup>2</sup> It is important to note that there are cases where corn producers are classified by PCIC as “self-financed,” but in reality these “self-financed” producers may also have production loans from informal lenders that require them to buy crop insurance (Reyes et al., 2015). It may be the case that this type of corn producers have had a bad credit history such that it would be difficult for them to get loans from formal sources.

season (wet vs. dry). Provinces are typically classified as low, medium or high risk depending on historical damage rates. Premium rates are higher for multi-risk cover (as compared to the natural disaster only cover) because it covers losses from pest and diseases in addition to losses from weather events. Wet season cropping is also associated with higher premium rates (relative to the dry season cropping) because wet season is when typhoons and floods usually occur. It should be noted, however, that PCIC premium rates have not been regularly updated over time (Reyes et al., 2015, p. 42). Since 1981, premium rates charged to farmers were only updated once in 2005.

When a loss event occurs due to a covered cause of loss, farmers need to file a Notice of Loss to the PCIC regional office. A team of adjusters will then verify the claim and only a loss over 10% of the expected yield would make the insured farmers eligible for indemnity payments. The insurance policy pays out indemnity in proportion to the percentage of loss due to specific insurable causes (as specified by the adjuster). For example, if the realized yield is just 70% of the expected yield for a farmer who insures the input cost (the minimum coverage required by the PCIC), then the indemnity payments will be equal to 30% of the input costs. In this case, the farmer's net income would be the total revenues from selling 70% of expected yield less 70% of the input costs (i.e., since 30% of input costs is paid back as indemnity).

### **Data**

The data set used in this study comes from a farm-level survey conducted in 2013 under a program called "Improving the Agricultural Insurance Program to Enhance Resilience to Climate Change." This program was administered by the Southeast Asian Regional Center for graduate study and research in agriculture (SEARCA). This survey covers three major corn growing provinces in the Philippines: Isabela, Pangasinan and Bukidnon. Farm households were selected using the multi-stage stratified random sampling approach. Two municipalities from each province were chosen with the criteria of larger areas devoted to corn production and larger numbers of producers enrolled in PCIC corn insurance program. The data on corn production

and number of insurance enrollees were obtained from the Bureau of Agricultural Statistics (BAS) and PCIC, respectively. In each sampled municipality, two villages with the largest numbers of insured farmers were chosen, and then, corn farmers in each village were stratified into insured and non-insured for the wet season (June-December) of the year 2012. The list of insured corn farmers was provided by PCIC and the list of non-insured farmers were obtained from village heads. In each stratum, 213 farmers were chosen randomly and a total of 426 corn producers were surveyed. The questionnaire elicits a wide range of farmers' information including the farmer's demographic background, socio-economic conditions, inputs used, farming and management practices, and some psychometric measures (such as risk-averseness). Nine farmers who stated they were just paid caretakers were dropped from the sample, because they did not make insurance purchase decisions. Three farmers said they had private or own insurance and did not purchase the natural disaster or multi-risk cover provided by PCIC, so these farmers were dropped as well. Moreover, three farmers who used open-pollinated seeds were also dropped as they are different from those who purchase commercial seed varieties.

### **Empirical Strategy**

Our empirical study includes two parts. One is to show the evidence that risk-averse farmers demand less insurance in the Philippines corn insurance market for the sample period studied, and the other one is to test whether risk-averse farmers turn to prefer the type of insurance that has little basis risk as predicted by insurance models with basis risk.

The fact that in this market, insured farmers include both the farmers who would voluntarily purchase insurance and farmers who were required by lenders to purchase it presents a challenge when it comes to estimating the farmers' real insurance demand. We leverage one question in our survey to overcome this hurdle. Specifically, one question in our survey asks "Would you have bought insurance if you were not required by the lender to purchase it?" Farmers who answered "yes" to this question are those who had true demand for crop insurance, while farmers who answered "no"

to this question were “forced” to purchase the crop insurance. Therefore, we estimate the following Probit model,

$$Pr(RealInsurance_i = 1|X_i) = \Phi(\beta_0 + \beta_1 X_i), \quad (8)$$

where  $RealInsurance_i$  denotes farmer  $i$ 's real demand for insurance, and  $X_i$  includes variables that may affect farmers' insurance demand, most importantly, the risk averseness measure. However, the survey question that is used to elicit farmers' real demand for insurance is only answered by insured farmers as implicitly we believe farmers who do not hold insurance have no demand for it. Hence, farmers' true demand for insurance is only observed for those farmers who hold the corn insurance. To make our estimation more rigorous and correct the potential sample-selection bias, we use the Probit model with sample selection described in detail in section 19.6.3 of Wooldridge (2010). The Probit model with sample selection extends the basic Heckman sample selection model (Heckman, 1979) to the case where the main equation of interest (demand equation in our case) is a Probit rather than a linear one. Therefore, we also consider a selection equation,

$$Pr(Insurance_i = 1|X_i, Z_i) = \Phi(\gamma_0 + \gamma_1 X_i + \gamma_3 Z_i), \quad (9)$$

where  $Insurance_i$  is farmer  $i$ 's insurance status, regardless being forced to hold or not, and  $Z_i$  includes variables that affect this selection equation but not the insurance demand equation. The sample selection bias arises when the two standard normally distributed random errors underlying (8) and (9) are correlated with correlation coefficient  $\rho$ . We estimate the Probit model with sample selection using the `heckprobit` command in Stata. In this case,  $RealInsurance_i$  is set to be missing for farmers who hold no insurance. However, as it is possible that uninsured farmers indeed have no demand for insurance, the Probit model without selection is applied as well in which  $RealInsurance_i$  is set to be 0 for uninsured farmers.

As for the second task in our estimation, we want to examine the impact of risk averseness on the demand for insurance with different levels of basis risk. Similar to our former methods, we estimate the real demand for the natural-disaster-only cover and the multi-risk cover, using the following Probit equations,

$$Pr(Realbasic_i = 1|X_i) = \Phi(\beta_0 + \beta_1 X_i),$$

and

$$Pr(RealMulti_i = 1|X_i) = \Phi(\beta_0 + \beta_1 X_i),$$

where  $RealBasic_i$  is set to be 1 if insured farmer  $i$  purchased the natural-disaster-only cover and answered “yes” to the question that elicits his true demand for insurance and 0 otherwise. Similarly,  $RealMulti_i$  is set to be 1 if insured farmer  $i$  purchased the multi-risk cover and answered “yes” to the question and 0 otherwise. As we know farmers’ true demand for either natural disaster or multi-risk cover once they have already hold this cover, therefore, we still use the selection equations,

$$Pr(Basic_i = 1|X_i, Z_i) = \Phi(\gamma_0 + \gamma_1 X_i + \gamma_3 Z_i),$$

and

$$Pr(Multi_i = 1|X_i, Z_i) = \Phi(\gamma_0 + \gamma_1 X_i + \gamma_3 Z_i),$$

where  $Basic_i$  denotes whether farmer  $i$  holds the natural disaster cover, and  $Multi_i$  the multi-risk cover. Therefore, we apply the Probit models with selection to examine factors impacting farmers’ real demand for the two cover types.

However, it is possible that farmers who hold neither covers have no demand for them, so there could be no selection bias. Hence, we also consider an ordered Probit model without selection correction,

$$Pr(Cover_i = j|X_i) = \Phi(\alpha_0 + \alpha_1 X_i - K_j) - \Phi(\alpha_0 + \alpha_1 X_i - K_{j+1}).$$

This equation represents the probability for farmer  $i$  to choose insurance coverage  $j$  conditional on his characteristics. If farmer  $i$  bought no crop insurance for the 2012 wet season or bought crop insurance but stated that he would not buy insurance if not required by his lender,  $Cover_i$  is set to be 0; If farmer  $i$  bought natural disaster insurance for the 2012 wet season and stated that he would buy insurance even if not required in accessing to credit,  $Cover_i$  is set to be 1; If farmer  $i$  bought multi-risk insurance and stated that he would buy insurance even if not required in accessing to credit,  $Cover_i$  is set to be 2. This variable represents a farmers’ true demand for insurance coverage as we group those farmers who do not purchase crop insurance and those who bought only to access credit together. Therefore, we estimate the

relationship between risk averseness and insurance demand for the two cases in which selection bias is either considered or not.

### *Variables and Summary Statistics*

Below we discuss the definition of each variable used in the equations and the reasons to include them. The variable of our main interest is the risk averseness measure (*RiskTolerance<sub>i</sub>*). Farmers' risk preference is measured by a hypothetical question asking whether they are willing to try a new seed variety that may double their yields or cut their yields by several given proportions (20%, 50% and 75%). Following the approach proposed by Kimball , Sahm, and Shapiro (2008), we use the

utility function with the constant relative risk aversion  $U(W) = \frac{w^{1-\frac{1}{\theta}}}{1-\frac{1}{\theta}}$  to calculate

the bounds of risk tolerance  $\theta$  for different answers. Those farmers who are not willing to try this risky seed even when it has half chance of decreasing their yields only by 20% are considered to be the most risk-averse ones, and *RiskTolerance<sub>i</sub>* is set to be 0.135 (the mid-point in the risk tolerance's range) for these farmers. Those farmers who are willing to try this risky seed when it has half chance of decreasing their yields by 30%/20% but not willing to when the loss is 50%/30% are given the value of *RiskTolerance<sub>i</sub>* of 0.75/0.385 for these farmers. The variable takes the value of 1 for the rest farmers who are willing to accept the most risky situation, that is, half change of lossing yield by half. Risk aversion affects insurance demand as our theoretical model shows, though the effect direction can be both ways.

The lagged yield per hectare (*Yield2011<sub>i</sub>*) could influence insurance demand. Goodwin (1993) found the lagged yield is inversely related to insurance demand as farmers are more likely to purchase insurance after yield shortfalls. Men and women are different both physically and psychologically, so the gender of the farm household's head (*Sex<sub>i</sub>*) can cause differences in insurance demand. Besides, older farmers are more experienced in farming and more confident in coping with farming risks, which can influence insurance purchase decisons. This is why age (*Age<sub>i</sub>*) is included as a control variable.



A cognitive ability indicator is included as another explanatory variable. Producers with high cognitive ability may find the insurance purchase process less burdensome and hence are more likely to purchase insurance (Reyes et al., 2015). The measure of cognitive ability used in this study was elicited using a word recall approach. Each respondent was asked to repeat a list of ten words, after listening to those words at the beginning and at the end of the interview. The total number of words (out of 20) the farmer could remember was recorded as his cognitive ability score ( $Cognitive_i$ ).

The variable  $DistanceRoad_i$  is the distance between farmer  $i$ 's farm and the nearest road. When disasters hit, fields closer to roads can receive immediate help while remote fields cannot. Therefore, fields that are far away from roads are riskier and farmers may demand more insurance.  $DistanceExt_i$  is farmer  $i$ 's distance to the nearest extension office. Farmers located closer to extension offices are more likely to receive information on both production techniques as well as risk management tools such as crop insurance. Therefore, this variable is included in the demand equations.

Organization membership ( $Org_i$ ) is equal to 1 if farmer  $i$  is a member of any organization, which includes farmers organizations, civic organizations, and religious organizations. Farmers with broader social networks through organization membership are likely to have an informational advantage on production techniques, as well as insurance products, compared with farmers with smaller social networks. In addition, crop insurance in the Philippines allows farmers to purchase crop insurance as a group, which may significantly reduce the burden of document preparation. Thus, this variable is included.

Land ownership variables are also included.  $FullOwner_i$  is a dummy variable for whether the farmer has full ownership of the planted lands. The omitted ownership category is for part owners, share tenants, leasehold or borrowed lands. Land ownership variables are used as explanatory variables for insurance demand in previous research (Goodwin, 1993). Therefore, this variable is included in  $X_i$ .

The total farming area is denoted as  $Area_i$ . It is expected that large farms are

associated with more farming assets, so this variable is used to test the effect of wealth on insurance demand.  $OtherCrop_i$  is set to be 1 if the farmer plants other crops aside from corn and 0 otherwise.  $Livestock_i$  is set to be 1 if the farmer raises any livestock and 0 otherwise. Whether a farm plants other crops and whether a farm raises livestock tell us how diversified the farm is. Farmers who grow other crops face less risk due to diversification. Therefore, diversification influences the insurance demand. For these reasons, these variables are included in our regressions.

Insurance premium rates only vary by province in the Philippines and they reflect the inherent risks in each province. Therefore, we use the province dummies as the control variables as well. Province dummy variables  $Isabela_i$  and  $Pangasinan_i$  are included in the insurance demand equations, and the Bukidnon province dummy is omitted.

To correct for the sample selection bias in the demand regressions, we also need to have a  $Z_i$  variable that affects insurance purchase but not the real demand. We believe the following variable is a good candidate. This variable is the amount of credit farmer  $i$  got ( $Credit_i$ ). Farmers who borrowed a lot were more likely to be required to purchase insurance, while the amount of borrowed money had little effect on their real demand for insurance. Table 1 lists all the variables used in our regressions and their definitions. Summary statistics for all the variables are reported in Table 2.

### **Estimation Results**

The parameter estimates and marginal effects for the insurance demand equations are presented in the Table 3. In the insurance demand Probit model with sample selection, it clearly shows that the more risk-tolerant farmers demand more insurance in this sample period. Though the result sounds surprising at first, considering our theoretical model, it is possible that farmers do not regard insurance as a product that decreases uncertainty in all circumstances due to basis risk. Therefore, only farmers who are more tolerant to the situation in which risk occurs but insurance pays nothing would prefer insurance.

Besides, farmers with better cognitive ability are more likely to purchase the insurance. Farmers with higher cognitive ability can better understand the benefits of this insurance and hence are more likely to purchase it. These high cognitive farmers are capable of perceiving the actual basis risk associated with the insurance product, while other low cognitive ones perceive larger basis risk due to cognition bias or lacking of trust. The results from the Probit model without selection are very similar, except that organization members are also found to present higher demand for insurance. Organizations create opportunities for farmers to interact and learn from each other, including knowledge on crop insurance. Organization members could also choose to insure their crop as a group, which would dramatically reduce the transaction costs associated with insurance application.

Results from the demand equations for the natural disaster cover and multi-risk cover respectively are reported in Table 4. We first discuss the result from the Probit model with sample selection for the natural disaster cover. It is found that farmers who are close to the nearest road have larger demand for the natural disaster cover. These farmers may have more information on insurance and understand its benefits.

There are also some interesting findings in the Probit model for the multi-risk cover. Again, the more risk tolerant farmers are found to present larger demand for this type of insurance. Contrary to the theoretical model, risk-averse farmers should have more preference for the cover with little basis risk. To reconcile the theory and the empirical finding, we speculate that farmers make insurance purchase decision based not on the actual basis risk but the perceived basis risk. It is not difficult to see that for those insurance products that claim to cover every risk, farmers may find them harder to believe into. Hence, multi-risk cover entails larger perceived basis risk. Finally, farmers who are closer to the extension offices are less likely to purchase the multi-risk cover insurance. These farmers have more opportunities to get information on pest and plant disease management from the extension agents, so they are less likely to purchase insurance that covers these risks.

We now turn to the ordered Probit model without sample selection. The results are in the same fashion to our previous findings. Farmers who are more risk-tolerant,

who are high-cognitive or who are organization members prefer more coverage. To sum up, we find the risk-tolerant farmers prefer more insurance as the theoretical model suggests, but farmers make purchase decision based on the perceived basis risk rather than the actual one. Therefore, farmers assign more “basis risk” to the complicated insurance product that claim to cover every risk.

#### *Robustness Check*

Another reason for the puzzle that risk averse farmers demand less insurance is that risk averse farmers substitute other precautionous measures for insurance, for example, by using more chemicals. To check whether it is the reason behind our finding, first, we show that risk averse farmers indeed use more chemicals, and second, we show that chemical use decisions have no correlation with insurance demand.

As insurance covers certain risks, which may affect farmers’ chemical use decisions, the uninsured sample is used to find the relationship between risk averseness and chemical use. We regress all the  $X_i$  variables on farmer  $i$ ’s per hectare use of fertilizers, weedicides, pesticides. The results are reported in Table 5. It can be seen that risk-averse farmers use more fertilizers. Then, we regress the  $X_i$  variables along with *Fertilizer* on farmers’ insurance demand. The results suggest that fertilizer use decisions have no correlation with insurance demand and risk-averse farmers still demand less insurance. Other significant coefficients make sense as well. Therefore, we believe the substitution story is not valid in explaining farmers’ insurance demand.

#### *Risk tolerance interaction effects*

Similar to Giné, Townsend, and Vickery (2007), which test the “product uncertainty” explanation by interacting risk aversion with social networking variables, and get the “correct” sign of risk aversion, we include the interaction term between risk tolerance and organization membership. The results are reported in Table 6. It is found that with organization membership, risk averse farmers demand more insurance

as predicted by classical insurance models (the P-value of coefficient of the interaction term is 0.10 in the Probit model with sample selection and below 0.10 for the model without selection). Therefore, it is a prevalent situation in the developing country that farmers perceive insurance as a product with uncertainty itself and they label larger “basis risk” to these insurance products.

### **Conclusion**

This research tests the usefulness of insurance models with basis risk to resolve the puzzle of low crop insurance demand among most risk-averse farmers in an indemnity insurance market. Its finding confirms the existence of the situation that risk-averse farmers demand less indemnity insurance than risk-tolerant ones, but farmers make purchase decisions based on the perceived basis risk instead of the actual one. Therefore, caution has to be taken when explaining behavior data in insurance markets. Anomalies can be caused by the actual or perceived basis risk of insurance products. Moreover, this research framework is an extension of the expected utility model of insurance from different amount of risk to different types of risks.

In addition, this result is especially useful for countries with low crop insurance demand. Implied by this result, a new direction to improve crop insurance program participation is to reduce farmers’ cognitive bias towards crop insurance, decrease the real or perceived basis risk, or increase their trust in insurance contracts. One possible future research direction is to extend this framework to explain the low adoption rate of new technology that is meant to decrease uncertainty among most risk-averse farmers.

### **References**

Cai, H., Y. Chen, H. Fang, and L. Zhou. 2014. “The Effect of Microinsurance on

- Economic Activities: Evidence from a Randomized Field Experiment.” *Review of Economics & Statistics* 97(2): 140814155137001.
- Carter, M. R., L. Cheng, and A. Sarris. 2016 “Where and How Index Insurance can Boost the Adoption of Improved Agricultural Technologies.” *Journal of Development Economics* 118: 59-71.
- Clark, D. 2016. “A Theory of Rational Demand for Index Insurance.” *American Economic Journal : Microeconomics* 8(1): 283-306.
- Cole, S., X. Giné J. Tobacman, P. Topalova, R. Townsend, and J. Vickery. 2013. “Barriers to Household Risk Management: Evidence from India.” *American Economic Journal: Applied Economics* 5(1): 104 -135.
- Doherty, N. A., and H. Schlesinger. 1990. “Rational Insurance Purchasing: Consideration of Contract Nonperformance.” *Quarterly Journal of Economics* 105(1): 243-253.
- Giné, X., R. Townsend, J. and Vickery. 2007. “Patterns of Rainfall Insurance Participation in Rural India.” *World Bank Economic Review* 22(3): 539-566.
- He, J. “Three Essays on Crop Insurance.” PhD dissertation. North Carolina State University, 2016.
- Kimball, M. S., C. R. Sahm, and M. D. Shapiro. 2008. “Imputing Risk Tolerance From Survey Responses.” *Journal of the American Statistical Association* 103(483): 1028-1038.
- Pratt, J. W. 1964. “Risk Aversion in the Small and in the Large.” *Econometrica* 32(1): 122-136.
- Reyes, C. M., C. D. Mina, R. A. B. Gloria, and S. J. P. Mercado. 2015. *Review of*

- Design and Implementation of the Agricultural Insurance Programs of the Philippine Crop Insurance Corporation*. Makati, Philippines: Philippine Institute for Development Studies, No. DP 2015-07, January.
- Reyes, C. M., R. A. B. Gloria, and C. D. Mina. 2015. *Targeting the Agricultural Poor: The Case of PCICs Special Programs*. Makati, Philippines: Philippine Institute for Development Studies, No. DP 2015-08, January.
- Ross, S. A. 1981. "Some Stronger Measures of Risk Aversion in the Small and the Large with Applications." *Econometrica* 49(49): 621-638.
- Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data, 2<sup>nd</sup> edition*. Cambridge, Massachusetts: The MIT Press.

Table 1 List of Variable

Variable	Unit	Definition
Sample Selection variables		
<i>Insurance</i>		=1 if held insurance in 2012, 0 otherwise
<i>Basic</i>		=1 if held the natural disaster only cover in 2012, 0 otherwise
<i>Multi</i>		=1 if held the multi-risk cover in 2012, 0 otherwise
Dependent variables		
<i>RealInsurance</i>		=1 if voluntarily purchased insurance, 0 otherwise
<i>RealInsurance</i> (censored)		=1 if voluntarily purchased insurance, 0 otherwise, missing values for uninsured farmers
<i>RealBasic</i>		=1 if voluntarily purchased the natural-disaster-only cover, 0 otherwise
<i>RealMulti</i> Cover		=1 if voluntarily purchased the multi-risk cover, 0 otherwise =0 if forced to purchase insurance or no insurance, =1 if voluntarily purchase natural disaster cover, and =2 if voluntarily purchase multi-risk cover.
Independent variables		
<i>RiskTolerance</i>		=1 for the most risk-tolerant farmers, and the midpoint of risk tolerance range otherwise
<i>Yield2011</i>	1000 kg/hectare	Reported yield per hectare for 2011
<i>Sex</i>		=1 if the household head is male, 0 otherwise
<i>Age</i>		Age of the household head
<i>Cognitive</i>	Number of words	Number of words recalled from 20 words by the farmer
<i>DistanceRoad</i>	Km	Distance to the nearest road
<i>DistanceExt</i>	Km	Distance to the extension office
<i>Org</i>		=1 if member in any organization and 0 otherwise
<i>FullOwner</i>		=1 if full owner of the land and 0 other tenure types
<i>Area</i>	Hectare	Total area of planted fields
<i>OtherCrop</i>		=1 if other crop aside from corn is planted and 0 otherwise
<i>Livestock</i>		=1 farmer raises any livestock and 0 otherwise
<i>Isabela</i>		=1 if in Isabela and 0 otherwise
<i>Pangasinan</i>		=1 if in Pangasinan and 0 otherwise
<i>Credit</i>	10,000 PHP	Total amount of loans



Table 2 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Insurance</i>	399	0.50	0.50	0	1
<i>Basic</i>	391	0.23	0.42	0	1
<i>Multi</i>	391	0.26	0.44	0	1
<i>RealInsurance</i>	399	0.23	0.42	0	1
<i>RealInsurance (censored)</i>	191	0.46	0.50	0	1
<i>RealBasic</i>	91	0.46	0.50	0	1
<i>RealMulti</i>	100	0.46	0.50	0	1
<i>Cover</i>	396	0.34	0.68	0	2
<i>RiskTolerance</i>	399	0.67	0.32	0.135	1
<i>Yield2011</i>	382	5.17	2.53	0	19.2
<i>Sex</i>	397	0.71	0.45	0	1
<i>Age</i>	396	47.66	11.68	23	87
<i>Cognitive</i>	398	7.26	3.43	0	20
<i>DistanceRoad</i>	389	0.95	1.83	0.0001	20
<i>DistanceExt</i>	365	12.61	10.58	0	50
<i>Org</i>	399	0.50	0.50	0	1
<i>FullOwner</i>	369	0.59	0.49	0	1
<i>Area</i>	392	2.50	2.34	0.25	26
<i>OtherCrop</i>	399	0.54	0.50	0	1
<i>Livestock</i>	399	0.15	0.36	0	1
<i>Isabela</i>	399	0.34	0.47	0	1
<i>Pangasinan</i>	399	0.33	0.47	0	1
<i>Credit</i>	398	3.06	3.66	0	34.5

Table 3 Demand Estimation for Insurance

	Insurance Demand: <i>RealInsurance</i> (Censored)			Insurance demand: <i>RealInsurance</i>	
	Sample Selection	Parameter Estimates	Marginal Effect	Parameter Estimates	Marginal Effect
<i>RiskTolerance</i>	0.1326 (-0.49)	0.7643* (-1.95)	0.2496* (-1.95)	0.5133* (-1.80)	0.1354* (-1.83)
<i>Yield2011</i>	0.0323 (-0.79)	0.0043 (-0.07)	0.0014 (-0.07)	0.0461 (-1.09)	0.0122 (-1.10)
<i>Sex</i>	0.0086 (-0.05)	-0.1304 (-0.49)	-0.0426 (-0.49)	-0.0483 (-0.25)	-0.0127 (-0.25)
<i>Age</i>	-0.0075 (-1.01)	0.0109 (-0.87)	0.0036 (-0.89)	-0.0032 (-0.41)	-0.0008 (-0.41)
<i>Cognitive</i>	0.0395 (-1.39)	0.0663* (-1.72)	0.0217* (-1.70)	0.0550** (-1.97)	0.0145** (-2.00)
<i>DistanceRoad</i>	0.0286 (-0.55)	0.0238 (-0.48)	0.0078 (-0.48)	0.0236 (-0.56)	0.0062 (-0.56)
<i>DistanceExt</i>	0.0041 (-0.44)	-0.0034 (-0.25)	-0.0011 (-0.25)	0.0003 (-0.03)	0.0001 (-0.03)
<i>Org</i>	0.9377** (-5.13)	-0.2315 (-0.59)	-0.0756 (-0.61)	0.6723** (-3.51)	0.1773** (-3.68)
<i>FullOwner</i>	-0.036 (-0.21)	-0.0403 (-0.17)	-0.0132 (-0.17)	-0.0854 (-0.48)	-0.0225 (-0.48)
<i>Area</i>	-0.0452 (-1.19)	-0.0966 (-1.24)	-0.0316 (-1.30)	-0.0199 (-0.48)	-0.0052 (-0.48)
<i>OtherCrop</i>	-0.0693 (-0.33)	0.3741 (-1.13)	0.1222 (-1.18)	-0.036 (-0.16)	-0.0095 (-0.16)
<i>Livestock</i>	0.1423 (-0.63)	-0.3891 (-1.26)	-0.1271 (-1.27)	-0.2077 (-0.86)	-0.0548 (-0.86)
<i>Isabela</i>	-0.4299* (-1.84)	1.1773** (-3.17)	0.3845** (-3.91)	0.5986** (-2.36)	0.1579** (-2.40)
<i>Pangasinan</i>	0.0738 (-0.27)	1.0790** (-2.70)	0.3524** (-2.77)	0.8632** (-3.00)	0.2277** (-3.09)
<i>Credit</i>	0.1896** (-6.66)				
<i>_cons</i>	-1.1831* (-1.90)	-1.7508* (-1.70)		-2.3340** (-3.60)	
<i>athrho</i>	-0.2056 (-0.43)				
N	311			313	

Notes: t statistics in parentheses; \*\*\*, \*\*, and \* indicate significant at 1 percent, 5 percent, and 10 percent

Table 4 Demand Estimation for Natural Disaster Cover and Multi-Risk Cover

	Insurance Demand: <i>RealBasic</i>			Insurance Demand: <i>RealMulti</i>			Insurance Demand: <i>Cover</i>		
	Sample	Parameter	Marginal	Sample	Parameter	Marginal	Parameter	Marginal Effect on	Marginal Effect on
	Selection	Estimates	Effect	Selection	Estimates	Effect	Estimates	Choosing Basic Cover	Choosing Multi-risk Cover
<i>RiskTolerance</i>	0.2046	0.0988	0.0297	-0.352	0.9558*	0.2709*	0.4839*	0.0427*	0.0816*
	-0.69	-0.12	-0.12	(-1.18)	-1.69	-1.79	-1.74	-1.73	-1.73
<i>Yield2011</i>	0.0465	-0.0423	-0.0127	-0.0275	-0.0176	-0.005	0.027	0.0024	0.0045
	-1.09	(-0.41)	(-0.43)	(-0.58)	(-0.16)	(-0.16)	-0.64	-0.64	-0.64
<i>Sex</i>	0.2403	-0.3643	-0.1094	-0.2879	0.2113	0.0599	-0.0749	-0.0066	-0.0126
	-1.19	(-0.67)	(-0.74)	(-1.43)	-0.47	-0.48	(-0.40)	(-0.40)	(-0.40)
<i>Age</i>	-0.0076	0.0212	0.0064	-0.0082	0.0102	0.0029	-0.0035	-0.0003	-0.0006
	(-0.92)	-1	-0.98	(-0.93)	-0.55	-0.56	(-0.45)	(-0.45)	(-0.45)
<i>Cognitive</i>	-0.0631**	-0.0298	-0.0089	0.1069**	0.1157	0.0328	0.0767**	0.0068**	0.0129**
	(-2.09)	(-0.29)	(-0.27)	-3.17	-1.24	-1.25	-2.86	-2.68	-2.83
<i>DistanceRoad</i>	0.0578	-0.1941*	-0.0583	-0.0035	0.1588	0.045	0.0379	0.0033	0.0064
	-1.38	(-1.77)	(-1.31)	(-0.07)	-1.29	-1.32	-0.92	-0.92	-0.92
<i>DistanceExt</i>	0.0033	-0.0302	-0.0091	-0.0075	0.0443*	0.0126*	0.0031	0.0003	0.0005
	-0.34	(-1.51)	(-1.19)	(-0.67)	-1.71	-1.87	-0.33	-0.33	-0.33
<i>Org</i>	0.1286	-0.2323	-0.0698	1.1587**	-0.3353	-0.095	0.7735**	0.0683**	0.1304**
	-0.64	(-0.45)	(-0.47)	-5.26	(-0.43)	(-0.43)	-4.1	-3.84	-3.92
<i>FullOwner</i>	-0.1535	-0.1719	-0.0516	0.1454	0.0415	0.0118	-0.0367	-0.0032	-0.0062
	(-0.84)	(-0.38)	(-0.35)	-0.76	-0.11	-0.11	(-0.21)	(-0.21)	(-0.21)
<i>Area</i>	-0.0481	0.0561	0.0169	-0.0433	-0.0987	-0.028	-0.0323	-0.0029	-0.0055
	(-0.86)	-0.37	-0.35	(-1.06)	(-0.84)	(-0.86)	(-0.78)	(-0.78)	(-0.77)
<i>OtherCrop</i>	0.2182	-0.276	-0.0829	-0.3651	0.7524	0.2132	-0.0087	-0.0008	-0.0015
	-0.93	(-0.50)	(-0.47)	(-1.47)	-1.35	-1.43	(-0.04)	(-0.04)	(-0.04)
<i>Livestock</i>	-0.0183	-0.1905	-0.0572	0.2221	-0.4652	-0.1318	-0.2082	-0.0184	-0.0351
	(-0.07)	(-0.36)	(-0.35)	-0.89	(-1.05)	(-1.05)	(-0.88)	(-0.88)	(-0.88)
<i>Isabela</i>	0.3894	0.9395	0.2822	-1.2364**	1.0084	0.2858	0.5051**	0.0446**	0.0852**
	-1.53	-1.19	-0.89	(-4.18)	-0.88	-0.9	-2.03	-2	-2.02
<i>Pangasinan</i>	-0.0691	0.002	0.0006	0.216	2.2075**	0.6256**	1.0144**	0.0896**	0.1710**
	(-0.23)	0	0	-0.69	-2.38	-2.62	-3.61	-3.37	-3.51
<i>Credit</i>	0.0600**			0.1084**					
	-2.41			-4.78					
<i>_cons</i>	-1.0349	0.6432		-1.071	-3.6701*				
	(-1.57)	-0.31		(-1.54)	(-1.74)				
<i>athrho</i>	-0.2302			-0.3131					
	(-0.20)			(-0.31)					
<i>cut1</i>							2.4870**		
							-3.93		
<i>cut2</i>							3.0175**		
							-4.71		
N	311			311			312		

Notes: t statistics in parentheses; \*\*\*, \*\*, and \* indicate significant at 1 percent, 5 percent, and 10 percent.

Table 5 Robustness Check

	Uninsured Sample			Insurance demand: <i>RealInsurance</i>	
	<i>Fertilizer</i>	<i>Weedicides</i>	<i>Pesticides</i>	Parameter Estimates	Marginal Effect
<i>RiskTolerance</i>	-0.5629** (-2.07)	-0.8115 (-1.40)	-0.1597 (-0.89)	0.5474* (-1.87)	0.1440* (-1.90)
<i>Yield2011</i>	0.1112** (-2.67)	0.3285** (-3.69)	0.0205 (-0.74)	0.0448 (-1.06)	0.0118 (-1.06)
<i>Sex</i>	-0.0051 (-0.03)	0.2654 (-0.62)	-0.1888 (-1.42)	-0.041 (-0.21)	-0.0108 (-0.21)
<i>Age</i>	-0.0012 (-0.16)	-0.0064 (-0.40)	0.0053 (-1.08)	-0.003 (-0.38)	-0.0008 (-0.38)
<i>Cognitive</i>	0.0213 (-0.65)	0.0214 (-0.31)	-0.0338 (-1.56)	0.0547** (-1.96)	0.0144** (-1.99)
<i>DistanceRoad</i>	0.0532 (-0.68)	-0.1344 (-0.80)	0.0865* (-1.66)	0.0207 (-0.49)	0.0055 (-0.49)
<i>DistanceExt</i>	-0.0105 (-1.07)	-0.0054 (-0.26)	-0.0225** (-3.48)	0.0003 (-0.03)	0.0001 (-0.03)
<i>Org</i>	0.4129** (-2.05)	0.3844 (-0.89)	0.0162 (-0.12)	0.6680** (-3.48)	0.1758** (-3.64)
<i>FullOwner</i>	-0.078 (-0.41)	-0.1426 (-0.35)	-0.0373 (-0.29)	-0.0891 (-0.50)	-0.0234 (-0.50)
<i>Area</i>	-0.0605 (-1.42)	-0.0676 (-0.74)	-0.0052 (-0.18)	-0.0215 (-0.52)	-0.0057 (-0.52)
<i>OtherCrop</i>	-0.5107** (-2.28)	-0.4707 (-0.98)	-0.2221 (-1.49)	-0.0218 (-0.10)	-0.0058 (-0.10)
<i>Livestock</i>	0.1655 (-0.62)	-0.3343 (-0.59)	0.0288 (-0.16)	-0.1984 (-0.82)	-0.0522 (-0.82)
<i>Isabela</i>	-0.4092 (-1.58)	-0.0367 (-0.07)	0.3367* (-1.96)	0.6251** (-2.41)	0.1645** (-2.46)
<i>Pangasinan</i>	1.5069** (-5.01)	-3.9509** (-6.16)	-0.4351** (-2.18)	0.8218** (-2.76)	0.2163** (-2.83)
<i>Fertilizer</i>				0.0389 (-0.55)	0.0102 (-0.55)
<i>_cons</i>	4.0881** (-6.35)	4.9497** (-3.61)	0.8356* (-1.96)	-2.5294** (-3.41)	
N	169	169	169	313	
R-sq/Pseudo R-sq	0.458722	0.363637	0.252401	0.132515	

Table 6 Estimation with Interaction Term of Risk Tolerance and Organization Membership

	Insurance Demand: <i>RealInsurance</i> (Censored)			Insurance demand: <i>RealInsurance</i>	
	Sample Selection	Parameter Estimates	Marginal Effect	Parameter Estimates	Marginal Effect
<i>RiskTolerance</i>	0.587 (-1.56)	1.9989** (-2.30)	0.3474** (-2.61)	1.1275** (-2.45)	0.1231 (-1.62)
<i>Org</i>	1.6000** (-3.92)	0.7038 (-0.88)	-0.0907 (-0.89)	1.4077** (-3.08)	0.1792** (-3.48)
<i>Org*RiskTolerance</i>	-0.9854* (-1.84)	-1.5816 (-1.64)		-1.0458* (-1.80)	
<i>Yield2011</i>	0.0316 (-0.77)	0.0047 (-0.08)	0.0014 (-0.08)	0.0473 (-1.12)	0.0123 (-1.12)
<i>Sex</i>	0.0305 (-0.16)	-0.0958 (-0.36)	-0.0292 (-0.36)	-0.0311 (-0.16)	-0.0081 (-0.16)
<i>Age</i>	-0.0083 (-1.12)	0.0128 (-1.04)	0.0039 (-1.06)	-0.0038 (-0.47)	-0.001 (-0.47)
<i>Cognitive</i>	0.0362 (-1.26)	0.0488 (-1.26)	0.0149 (-1.24)	0.0526* (-1.88)	0.0137* (-1.90)
<i>DistanceRoad</i>	0.0397 (-0.73)	0.0183 (-0.37)	0.0056 (-0.37)	0.0294 (-0.69)	0.0077 (-0.69)
<i>DistanceExt</i>	0.0022 (-0.23)	-0.0068 (-0.50)	-0.0021 (-0.51)	-0.0007 (-0.07)	-0.0002 (-0.07)
<i>FullOwner</i>	-0.0641 (-0.37)	-0.1136 (-0.48)	-0.0346 (-0.48)	-0.1199 (-0.67)	-0.0313 (-0.67)
<i>Area</i>	-0.0524 (-1.36)	-0.1001 (-1.32)	-0.0305 (-1.37)	-0.0221 (-0.54)	-0.0058 (-0.54)
<i>OtherCrop</i>	-0.0512 (-0.24)	0.391 (-1.22)	0.1191 (-1.26)	-0.0273 (-0.12)	-0.0071 (-0.12)
<i>Livestock</i>	0.1798 (-0.78)	-0.3276 (-1.07)	-0.0998 (-1.07)	-0.1658 (-0.68)	-0.0433 (-0.68)
<i>Isabela</i>	-0.4535* (-1.91)	1.0652** (-2.95)	0.3244** (-3.25)	0.5808** (-2.25)	0.1516** (-2.29)
<i>Pangasinan</i>	0.0414 (-0.15)	0.9711** (-2.42)	0.2957** (-2.42)	0.8567** (-2.96)	0.2236** (-3.06)
<i>Credit</i>	0.1941** (-6.70)				
<i>_cons</i>	-1.3793** (-2.16)	-2.1750* (-1.87)		-2.7084** (-3.90)	
<i>athrho</i>	-0.445 (-0.87)				
N	311			313	