ABSTRACT

HE, JUAN. Three Essays on Crop Insurance. (Under the direction of Xiaoyong Zheng and Roderick Rejesus.)

These research studies are aimed to provide valuable information on the development of sustainable crop insurance programs especially for developing countries. Chapter 1 points out that similar to evidences in other markets, empirical research in the crop insurance market implies the classical model of insurance fails to describe the possible multi-dimensions of private information that could potentially benefit both insurers and the insured. The classical model predicts that due to private information on risk types, high-risk agents are more likely to purchase insurance, making the pool of the insured riskier as premium rates increase. However, a theoretical model shows that it is possible to see risk-averse farmers have more demand for insurance and have low risk at the same time - the "advantageous selection." The results confirm this prediction and suggest that in the Philippines' crop insurance market, farmers who use hybrids instead of genetically modified seed have higher productivity and tend to purchase insurance. The application of a multidimensional selection model in crop insurance programs could be an important future research topic.

Chapter 2 investigates the effectiveness of monitoring on reducing moral hazard, which is one of the big problems in crop insurance. In the Philippines' insurance market, farmers are monitored by technicians to ensure that they follow their farming plans as stated in their insurance application documents. A theoretical model is set up and predicts that as their farming decisions are observed, farmers increase use of certain inputs under insurance coverage. The intuition is that farmers tend to make more investment into production as their expected loss is decreased. The empirical result is consistent with this prediction that insured farmers use more fertilizers, weedicides as well as spend more on chemical inputs. This

finding suggests that monitoring can be incorporated into insurance programs in order to promote productivity growth in the agricultural sector.

As two main problems in crop insurance, adverse selection and moral hazard are empirically difficult to separate from each other. Chapter 3 utilizes a survey question to distinguish adverse selection from moral hazard effects. This question asks whether a farmer is willing to purchase insurance if it is not required for accessing loans. The answers to this question make it possible to estimate adverse selection by comparing the farmers who select insurance voluntarily with those who are forced to get insured, and estimate moral hazard by comparing the insured farmers that are forced to purchase insurance with the non-insured farmers. The results suggest that though monitoring is effective in combating certain moral hazard behaviors, the final effect of insurance on yield could still be ambiguous. There is also evidence suggesting that farmers have private information on the occurrences of pest infestation or plant diseases, so a minimum level of chemical use could be required for insurance purchase.

Three Essays on Crop Insurance

by
Juan He

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Economics

Raleigh, North Carolina

2016

APPROVED BY:

Xiaoyong Zheng Committee Co-Chair	Roderick Rejesus Committee Co-Chair
Tomislav Vukina	Barry Goodwin

DEDICATION

To my late friend, Wangcai Shi, who loved me unconditionally despite my grades;

To my parents, the doctors;

To my maternal grandparents, the doctors too;

To my paternal grandparents, who would have preferred a grandson;

To Ruiz, Landa, the best friends one could ever hope for;

To my advisor Prof. Zheng, for preparing me to start an academic career;

And to my beloved Xiaofan He, who wants to be the last one on this page.

BIOGRAPHY

Prior to completing the Ph.D. in economics at North Carolina State University, Juan He finished a double-degree program in Europe under the EU Erasmus Mundus scholarship. Ms. He received an MS in business economics from the University of Amsterdam and an MS in financial management from the University of Ljubljana in 2011. Before starting graduate study, she earned a BS in finance at Shanghai University of International Business and Economics and was awarded first-class scholarships for outstanding academic achievement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Advantageous Selection in Crop Insurance: Evidence from the Philippines

Introduction

Classical models of insurance predict that asymmetric information can lead to a positive correlation between insurance coverage and ex post realizations of loss (Rothschild and Stiglitz, 1976). One possible explanation for this is the so-called adverse selection problem, where more risky individuals are the ones who are more likely to purchase insurance or purchase more insurance.[1] However, empirical studies of various insurance markets including auto, life and long-term care insurance markets failed to find the aforementioned positive correlation between insurance coverage and realization of loss.[2]

To reconcile the seemingly contradictory results from the classical asymmetric information insurance models vis-à-vis the empirical literature, de Meza and Webb (2001) developed an alternative theoretical framework where the insureds' informational advantage about their risk type is assumed to be multi-dimensional, as opposed to the one-dimensional assumption used in classical models. For example, in de Meza and

[1] Another possible reason is moral hazard where the insured are more likely to engage in risky activities because they have coverage.

[2] These empirical studies include Dionne, Gourieroux, and Vanasse (1998), Chiappori and Salanie (2000), and Dionne, Gourieroux, and Vanasse (2001) for automobile insurance markets, Cawley and Philipson (1999) and McCathy and Mitchell (2010) for life insurance markets, Davidoff and Welke (2005) for reverse mortgage markets and Finkelstein and McGarry (2006) for long-term care insurance markets.

Webb (2001), the informational advantage of the insureds is assumed to be two-dimensional – the insured has private information with regards to both his/her inherent riskiness and his/her degree of risk aversion. In a partial pooling equilibrium, they showed that the insureds who are more risk averse would demand more coverage and at the same time have lower risks, i.e., risk aversion causes a negative correlation between insurance coverage and realization of loss. This phenomenon is termed as "advantageous selection" and factors that cause this phenomenon are called "sources of advantageous selection." On the other hand, the insureds who have higher inherent riskiness would demand more coverage and at the same time have higher risks, that is, the adverse selection force in classical models is still at play. As a result, a positive correlation between insurance coverage and realization of loss may not be observed in the data if the advantageous selection effect dominates the adverse selection effect.

The goal of this study is to examine the existence and identify the sources of advantageous selection in crop insurance. To the best of our knowledge, our paper is the first effort to do so. Previous studies of crop insurance markets focused on adverse selection and/or moral hazard. See Goodwin (1993), Quiggin, Karagianis, and Stanton (1993), Smith and Baquet (1996), Just, Calvin and Quiggin (1999), Makki and Somwaru (2001), Garrido and Zilberman (2008), Hou, Hoag, and Mu (2011) for studies of adverse selection; Smith and Goodwin (1996), Knight and Coble (1997), and Roberts, Key, and O'Donoghue (2006) for studies of moral hazard. There have also been empirical studies of advantageous selection in other insurance markets. See Finkelstein and McGarry (2006) for the long-term care insurance market and Fang, Keane and Silverman (2008) for the

Medigap insurance market. But there have been no studies of advantageous selection in the crop insurance market.

Identifying the sources of advantageous selection in crop insurance has important policy implications. Crop insurance is widely regarded as a crucial institutional mechanism in improving farmers' welfare as well as ensuring food security. However, participation rates in crop insurance programs have been consistently lower than desired, especially in some developing countries such as the Philippines where the majority of farmers are still poor. Once a farmer/farm characteristic is identified as a source of advantageous selection, premium discounts can be offered to farmers with such a characteristic. This would induce more farmers with this characteristic to participate in the crop insurance program and at the same time, the actuarial performance of the program would increase because these farmers are less risky. With a healthier balance sheet, premiums can also be reduced for other farmers to boost the participation rate even further.

Using data from a survey of corn farmers in the Philippines, we identify utilizing hybrid seeds instead of genetically modified seeds as a source of advantageous selection into the Philippine crop insurance program.[3] Using the traditional hybrid seeds rather than the more uncertain genetically modified seeds reflects those farmers being more cautious and hence they are more likely to purchase crop insurance. At the same time, we find

[3] In the context of the Philippines, the genetically modified seeds (i.e., genetically modified organism (GMO)) are corn varieties with the Bacillus thuringensis (Bt) gene in it that makes it resistant to Asian corn borer. Some of the GMO/Bt corn crops at the time of the survey also contains an additional herbicide tolerant trait which allows for more application of herbicides without (to control weeds) without adversely affecting the corn plant.

they are also more productive. Therefore, this group of farmers advantageously self-select into the crop insurance program.

The rest of the paper is organized as follows. The next Section describes the conceptual framework on which our empirical analysis is based. 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: Advantageous Selection in Crop Insurance

To illustrate advantageous selection within a crop insurance context, we develop a simple model of crop insurance purchase decision. . We assume that there are two types of producers, one "bold" and the other one "cautious." We follow De Meza and Webb (2001)'s approach of describing the bold type by a "α", the degree of boldness.[4] 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 decreasing $-\frac{U''}{U'}$ in w, which implies decreasing absolute risk-aversion. The bold type behaves as if they had α units more wealth than the

[4] The two types have different tastes and hence different utility functions but their differences can be characterized by the same utility function with different wealth levels.

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 and loss occurs, then he will receive an indemnity payment of L.[5]

With these assumptions, the expected utility for the representative farmer i when he does not purchase insurance can be written as,

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

where $w_0 = w$ if the farmer is a cautious type and $w_0 = w + \alpha$ is a bold type.[6] His expected utility when he purchases insurance is,

$$EUI_i(w_0) = U(w_0 - y),$$

where y is the insurance premium. As a result, farmer i will participate in crop insurance if $EU_i(w_0) < EUI_i(w_0)$ and there is a threshold no-loss probability $\bar{p}$ such that the farmer is indifferent between participating in the crop insurance program or not, that is,

(1) $$EU_i(w_0) = \bar{p}U(w_0) + (1 - \bar{p})U(w_0 - L) = EUI_i(w_0) = U(w_0 - y).$$

Farmers with no-loss probabilities that are lower than $\bar{p}$ will purchase crop insurance. We are now ready to state the following theorem,

[5] No partial coverage is assumed for brevity purpose. The proofs can be extended to a model with partial coverage (see Appendix A).
[6] Again, for brevity purpose, we assume w and α are the same for all farmers.

THEOREM 1 (ADVANTAGEOUS SELECTION): The threshold no-loss probability for the cautious type is higher than that of the bold type, that is, $\bar{p}_C > \bar{p}_B$.

PROOF: From (1), we have,

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

Since the premium y is typically a small number compared with the wealth w_0, the equation above can be rewritten as,

$$\bar{p} = 1 - y\frac{U'(w_0)}{U(w_0) - U(w_0 - L)}.$$

Therefore, we have $\bar{p}_C = 1 - y\frac{U'(w)}{U(w)-U(w-L)}$ and $\bar{p}_B = 1 - y\frac{U'(w+\alpha)}{U(w+\alpha)-U(w+\alpha-L)}$. Hence, to prove $\bar{p}_C > \bar{p}_B$, it's equivalent to prove,

$$1 - y\frac{U'(w)}{U(w) - U(w - L)} > 1 - y\frac{U'(w + \alpha)}{U(w + \alpha) - U(w + \alpha - L)}.$$

If we can show that the above inequality holds for a small positive number for any w, then it is clear that the inequality will also hold for any positive α (since we can divide α into many positive small increments and each time we can move a small step from w towards $w + \alpha$ without violating the above inequality). So in the rest of the proof, we work with the case where α is a very small positive number. When α is small, the above inequality can be rewritten as,

$$\frac{U'(w)}{U(w) - U(w - L)} < \frac{U'(w) + \alpha U''(w)}{U(w) - U(w - L) + \alpha[U'(w) - U'(w - L)]},$$

which can be further simplified to be,

(2) $$\frac{-U'(w)+U'(w-L)}{U(w)-U(w-L)} > \frac{-U''(w)}{U'(w)}.$$

Therefore, to prove $\bar{p}_C > \bar{p}_B$, it's equivalent to prove inequality (2).

We now prove (2). Since L could be very large compared with w in the context of the agricultural sector in most developing countries,[7] we cannot assume it is a small number. Instead, we let $L = \sum_{j=1}^{n} L_j$, where each L_j is a small positive number. (2) can then be rewritten as:

$$\frac{-U'(w) + U'(w - L_1) - U'(w - L_1) + U'(w - L_1 - L_2) \ldots + U'(w - L)]}{U(w) - U(w - L_1) + U(w - L_1) - U(w - L_1 - L_2) \ldots - U(w - L)} > \frac{-U''(w)}{U'(w)},$$

or

$$\frac{\sum_{j=1}^{n}\left[-U'(w_j) + U'(w_j - L_j)\right]}{\sum_{j=1}^{n}\left[U(w_j) - U(w_j - L_j)\right]} > \frac{-U''(w)}{U'(w)}.$$

where $w_j = w_{j-1} - \sum_{k=1}^{j-1} L_k$, $j = 2, 3 \ldots n$ and $w_1 = w$. Since each L_j is small, we have,

$$\frac{-U'(w_j) + U'(w_j - L_j)}{L_j} = -U''(w_j - L_j),$$

and,

$$\frac{U(w_j) - U(w_j - L_j)}{L_j} = U'(w_j - L_j).$$

Thus,

$$\frac{-U'(w_j) + U'(w_j - L_j)}{U(w_j) - U(w_j - L_j)} = \frac{-U''(w_j - L_j)}{U'(w_j - L_j)}.$$

[7] This is especially true in the Philippines where one extreme weather event, such as a major typhoon, would make it very difficult for poor farmers in the rural areas to recover from the losses associated with this weather event (Reyes et al., 2015). This is why one of the main purposes of the Philippines crop insurance program is to ensure farmers' financial ability to restart their farming business after major losses from natural disasters occur.

Since -$\frac{U''}{U'}$ is a decreasing function, for all j, we have,

(3) $$\frac{-U'(w_j)+U'(w_j-L_j)}{U(w_j)-U(w_j-L_j)} = \frac{-U''(w_j-L_j)}{U'(w_j-L_j)} > \frac{-U''(w)}{U'(w)}.$$

In addition, since $U' > 0$, and $U'' < 0$, we also know that, $-U'(w_j) + U'(w_j - L_j) > 0$, and $U(w_j) - U(w_j - L_j) > 0$. Therefore, using (3), we have,

$$\frac{-U'(w) + U'(w-L)}{U(w) - U(w-L)} = \frac{\sum_{j=1}^{n}\left[-U'(w_j) + U'(w_j - L_j)\right]}{\sum_{j=1}^{n}\left[U(w_j) - U(w_j - L_j)\right]} > \frac{-U''(w)}{U'(w)}.$$

This completes the proof.

REMARK: The fact that $\bar{p}_C > \bar{p}_B$ means that cautious farmers are more likely to purchase crop insurance than bold farmers because they have a higher no-loss probability threshold to not purchase crop insurance. At the same time, because of the uniform distribution assumption, the average probability of no-loss for the insured bold farmers is $\bar{p}_B/2$, smaller than the average probability of no-loss for the insured cautious farmers, that is, $\bar{p}_C/2$. As a result, the insured cautious farmers are less likely to have a loss than the insured bold farmers. In summary, the cautious farmers are more likely to purchase crop insurance but less likely to experience a loss once insured. This type of selection benefits the insurer and hence is called advantageous selection.

From Theorem 1, we can derive the following corollary,

Corollary (WEALTH EFFECT): For the same type of farmers, a farmer with lower wealth is more likely to purchase crop insurance.

PROOF: In Theorem 1, we proved that cautious farmers are more likely to purchase crop insurance than bold farmers. By construction, in our model, the bold farmers act as if they

had more wealth. Therefore, the proof in Theorem 1 can also be used to prove farmers with lower wealth are more likely to purchase crop insurance.

Finally, we have the following Theorem,

Theorem 2 (ADVERSE SELECTION): For two farmers of the same type and with the same amount of wealth w_0, the one with a lower no-loss probability is more likely to purchase insurance and is also more likely to experience a loss if insurance is bought. This is called adverse selection in the literature.

PROOF: Suppose there are two farmers of the same type and with the same amount of wealth w_0. One farmer has the no-loss probability of p_L and the other had the no-loss probability of p_H with $p_H > p_L$. As discussed above, a farmer will purchase crop insurance if his no-loss probability is less than threshold probability $\bar{p}$. Since $p_H > p_L$, we have $Pr(\bar{p} > p_L) > Pr(\bar{p} > p_H)$. Therefore, the farmer with lower no-loss probability is more likely to purchase crop insurance. The second part of this corollary is trivial. Since $p_H > p_L$, by definition, the farmer with a lower no-loss probability is more likely to experience a loss if insured. This completes the proof.

Before we turn to the empirical analysis to test the hypotheses stated above, it is worth noting that although we term the two types of farmers in our model as cautious and bold, cautiousness is not the only possible source of advantageous selection. The Corollary above clearly shows another source of advantageous selection is being less wealthy. In general, as long as a certain characteristic makes one type of farmers to act as if they had less wealth than the other type, the model and the proofs above can be applied to show that this characteristic is a source of advantageous selection. For example, one

possibility is that people who have higher cognitive ability can perceive more dangers and hence act as if they had less money. As for the adverse selection, our model is also very general in terms of the source of the adverse selection. As long as a characteristic makes the farmer have a lower no-loss probability given other things, it can be called a source of adverse selection.

Background

The agricultural industry has been recognized by the Philippine 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), weather shocks are the major factor that contributes to impoverishment in the Philippines. Farmers could mitigate the impact of 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 suitable during recent years when farmers have been confronted with new 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. 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).[8] 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.[9]

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

[8] 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.

[9] 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.

yield, with the approval of the PCIC. However, it should be noted that the PCIC corn insurance product is subject to the following liability ceilings: (a) PHP 40,000/USD 948[10] per hectare for hybrid and GMO corn varieties, and (2) PHP 28,000/USD 664 per hectare for open-pollinated varieties.

Reyes et al. (2015) points 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 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) 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.

The Philippine government heavily subsidizes corn insurance premiums. The government pays more than 50% of the total insurance premium for corn. Lending institutions also share a portion of the premium if the insured farmer borrows from them (i.e., the borrower client). Therefore, the borrower clients' premiums are shared among

[10] The average 2012 exchange rate was 0.023 USD/PHP.

the lending institution, the government, and the farmers themselves. The self-financed clients' premiums, on the other hand, are only shared with the government. But note that the total premium rate is typically the same for both the borrowing and the self-financed farmers.[11] In addition, the government's share is also the same for both types of farmers. This arrangement means that self-financed clients have to pay an additional amount of premium (relative to the borrower clients), which is equivalent to what would have been assumed by lending institutions if they were borrower clients.

The premium rate shared by the lending institution and the government is also constant across different types of insurance cover (i.e., natural disaster vs. multi-risk) as well as different risk classifications (i.e., low vs. medium vs. high). This scheme implies that the premium rate paid by the lending institutions and the government remains the same for farmers with different risk classification levels and the additional premium for being high risk will have to be borne by the high-risk farmer themselves. For example, the premium rate (premium as a percentage of liability) paid by a self-financed corn farmer classified as high risk is 11.48% and the government pays 10.62%; while a low risk farmer only pays 5.83% himself with the government still paying 10.62%.

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% 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).

[11] See the PCIC table of national composite premium rates and premium sharing schemes of the corn insurance program at: http://pcic.gov.ph/index.php/insurance-packages/corn-crop-insurance/.

From 1982 to 1990, the PCIC corn insurance program had a difficult time when the total claim amount consistently exceeded total premium collected. Since 1990, the situation has been reversed and total premiums are now much larger than the indemnities paid. In 2012, the total premium was two times larger than the total indemnities paid out to producers. In addition, the number of insured farmers had declined from the peak at 40,410 in 1990 to 3,910 in 2007. However, after 2007, the number of insured farmers has steadily increased and reached 12,271 in 2012. This growth in participation may be attributed to the increased frequency of natural disasters during that period. As a result, farmers may have had an increasing awareness of the importance of insurance. This growth in participation may also be ascribed to the promotion of various new largely-subsidized special crop insurance programs during this period. These special programs were officially launched in 2012 (Reyes, Gloria and Mina, 2015).

In 2012, 29% of the insured farmers had indemnities paid from the PCIC corn crop insurance program. As for the causes of loss, typhoons, floods and droughts were the main causes. For example, in 2012, an indemnity of PHP 15.77/USD 0.374 million was paid for losses due to typhoons or floods, while PHP 4.53/USD0.107 million and PHP 6/USD 0.142 million were paid for losses due to pests and diseases, respectively. In general, the losses caused by natural disasters are more than twice the losses caused by pests or diseases (Yorobe and Luis, 2015).Therefore, seasonal climate variability and occurrence of adverse weather events are the main sources of uncertainty for corn farmers in the Philippines.

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 for the survey using the multi-stage stratified random sampling approach. Two municipalities from each province were chosen based on the area devoted to corn production and the number of producers enrolled in PCIC corn insurance program. The data on the area devoted to corn and the number of insured producers 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. In each stratum, 213 farmers were chosen randomly. The list of insured corn farmers was provided by PCIC and the list of non-insured farmers were obtained from village heads. 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 indicators of cognitive ability and cautiousness).

Empirical Strategy

We build on Finkelstein and McGarry (2006)'s approach in developing the estimation strategy. They estimated two probit models simultaneously to find the possible sources for advantageous selection in the long-term care insurance market. One probit model uses insurance purchase as the dependent variable and the other one uses risk occurrence (e.g., measured as the number of times medical services are used; more medical services means the insured is more risky). Conditional on risk classification (as determined by the insurer), if an independent variable is found to be positively correlated with insurance purchase and negatively correlated with risk occurrence, they say this variable is a source of advantageous selection. It is because the person with this feature tends to buy insurance but has low risk level. On the other hand, if a variable is found to be positively correlated with insurance purchase and risk occurrence at the same time, this variable is called a source of adverse selection. In the crop insurance market, a natural measure of risk occurrence is yield performance (in kg/ha) of the farm during the cropping season of interest (i.e., higher yields means the insured is less risky while lower yields means the insured is more risky). Therefore, in the context of crop insurance, the two regression models are as follows

(4) $$Yield_i = \beta_0 + \beta_1 X_i + \beta_2 RiskClassification_i + \varepsilon_i$$

(5) $$Pr(Insurance_i = j | X_i,\ RiskClassification_i) = \Phi\big(\alpha_0 + \alpha_1 X_i + \alpha_2 RiskClassification_i - К_j\big) - \Phi\big(\alpha_0 + \alpha_1 X_i + \alpha_2 RiskClassification_i - К_{j+1}\big),$$

where $Yield_i$ is farmer i's yield (in kg per hectare) for the 2012 wet cropping season, X_i represents farmer i's characteristics variables, $RiskClassification_i$ is farmer i's risk classification level as determined by the insurer, and ε_i is the error term.

Equation (5) represents the probability for farmer i to choose insurance coverage j conditional on his characteristics as implied by an ordered Probit model. 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, $Insurance_i$ 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, $Insurance_i$ 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, $Insurance_i$ 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. Finally, as some unobserved variables could influence yield performance and insurance choice at the same time, simultaneous estimation of the two equations is implemented to allow for correlated error terms.

As mentioned earlier, there are three levels of risk classification assigned by PCIC for each insured. They are low, medium and high. Because of the expected high probability of typhoon in 2012, the PCIC assigned a high risk classification for all the farmers in our 2012 sample. However, since premium rates vary by province in the Philippines and premium rates reflect the inherent risk in each province, we use the province dummies as the risk classification variables. These dummies are included in

both the yield performance and the insurance selection equations. Since premium rates only vary by location in our survey data, each variable in the vector X_i can be a potential source of selection. The vector X_i includes farmer i's characteristics that can potentially influence one or both of the dependent variables of interest. Below we discuss the definition of each variable and the reasons to include them in the regressions.

Since each farmer has land with different quality, faces different weather conditions, and uses different technology, we include the average yield per hectare of the two most recent years, that is, 2010 and 2011, ($HistoricalYield_i$) in the regressions to control for unobserved individual heterogeneity that are not captured by the province dummies.[12] In addition, the average historical yield reflects the deterministic farming conditions that are persistent across years. It also influences the insurance purchase decision. Goodwin (1993) found the lagged yield is inversely related to insurance demand as farmers are more likely to purchase insurance after yield shortfalls. Thus, this variable is included in both the yield and the insurance choice regressions.

More safety-conscious farmers are less likely to get injured when farming. As a result, they are healthier and more productive. Moreover, these safety-conscious farmers may be more likely to buy insurance because the reason for them being more safety-conscious might be they are more cautious or risk averse. Thus, a safety-conscious indicator, $Safety_i$ is included in both regressions. The variable $Safety_i$ comes from the survey question on whether the farmer uses or does not use his/her bare hands to handle

[12] For those respondents who could not recall the yields of these two years, the values for this variable are denoted as missing.

chemicals used in production (i.e., =1 if the farmer uses gloves when handling chemicals and 0 otherwise).

The variable $Label_i$ comes from the survey question on whether the farmer reads the labels of chemicals before application (i.e., =1 if reads labels and 0 otherwise). Instructions on the label tell farmers the correct way to apply the chemicals to their fields and those who follow the instructions are likely to be more productive. Also, these farmers may be more likely to buy insurance because reading labels carefully indicates they are more willing to follow other people's advice and hence are more likely to respond to government's crop insurance promotion campaign. Therefore, this variable is included in both regressions.

A cognitive ability variable is also included in both regressions. Farmers with high cognitive ability tend to be more productive and are also better equipped to go through complicated insurance application process. Reyes et al. (2015) mention that insured farmers complained about the highly technical and tedious procedures for insurance purchase. Producers with high cognitive ability may find this process less burdensome and hence are more likely to purchase insurance. 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 for two times. One is at the beginning and the other one is 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 ($Cognitive_i$).

Another variable included in the regressions is whether hybrid (non-GMO) seeds are used in production. The $Hybrid_i$ variable is equal to 1 if farmer i uses hybrid seeds and 0 if GMO or BT seeds are used.[13] Newly developed GMO and BT seeds offer various new features, such as inherent resistance to pests (i.e., Asian corn borers) and herbicide tolerance (i.e., to be able to apply more herbicides to control weeds without damaging the plant),. Therefore, the type of seed used is a determinant of the yield. Also, GMO and BT seeds are relatively new with a lot of uncertainty. Farmers who adopt them are the bold type and are less likely to purchase crop insurance. For these reasons, this variable is included in both regressions.

The variable $DistanceRoad_i$ is the distance between farmer i's fields and the nearest road. Better access to roads allows farmers to take better care of their fields and hence yields are likely to be higher. Also, when disasters hit, fields closer to roads can receive immediate help while remote fields cannot. Therefore, fields that are far away from roads are more risky and farmers may demand more insurance for these fields. Therefore, this variable is included in both regressions.

$DistanceExt_i$ 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 the crop insurance. Therefore, this variable is included in both regressions.

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

[13] Three farmers who used open-pollinated varieties were dropped from this sample.

organizations. Farmers with social networks are likely to have informational advantage on production techniques as well as insurance products compared with farmers with little social networks. In addition, the corn 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 both models.

Land ownership variables are also included. $FullOwner_i$ is the dummy variable for whether the farmer has full ownership of the planted fields and $PartOwner_i$ is the dummy variable for whether the farmer has partial ownership of the fields. The omitted ownership category is mortgage, share tenant, leasehold or borrowed land. Land ownership variables are used as explanatory variables for insurance demand in previous research (Goodwin, 1993) as farmers in greater debt are more likely to be required to purchase insurance. Furthermore, farmers with partial or no land ownership may have very different incentives in production than those with full ownership. Therefore, these variables are included in both regressions.

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 wealth effect on insurance demand and yield performance as predicted by the theoretical model. Years in corn farming is denoted as $Experience_i$. This variable is used to control for different levels of acquired skills and knowledge from corn producing experience. It may also affect insurance adoption because an experienced farmer would be more confident and know alternative methods of mitigating farming risks. Thus, this variable is included in both models.

$OtherCrop_i$ 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. A specialized farmer in corn production might be more productive due to specialization. On the other hand, farmers who grow other crops or raise livestock face less risks due to diversification. In addition, the damage from corn-borne pests and diseases are more likely to be restricted to the corn planted parcel. Therefore, diversification influences the insurance demand. For these reasons, these two variables are included in both regressions.

The amount of loan ($Credit_i$) has direct impact on the insurance demand. Farmers borrow money from banks, cooperatives, relatives, traders and other sources. Farmers who borrow more may be under pressure and are more likely to purchase crop insurance because they want to make sure the loan can be paid back. Therefore, the amount of loan is included in the insurance demand regression.

Table 1.1 lists all the variables used in our regressions and their names and definitions. Summary statistics for all the variables are reported in Table 1.2. The mean values for the variables are similar across non-insured and insured subsamples except for a few variables. Insured farmers borrow on average 10,000 PHP more than farmers without insurance. Farmers who enroll in the corn insurance program have significantly higher cognitive ability than non-insured. Insured farmers have farms that are located farther away from the nearest road. Finally, there is a significantly larger portion of insured farmers who are members of organizations.

Results

The parameter estimates for the baseline regressions are presented in Table 1.3. Panel A collects the results for the full sample and Panel B is for the insured subsample. These baseline models include only the risk classification variables used by the PCIC, which are the province dummies. The results from both the full and the insured subsample show that yields are more than two thousand kilograms per hectare higher in Isabela and more than four thousand kilograms per hectare higher in Pangasinan, compared with Bukidnon. Given that the provinces of Isabela and Pangasinan are located in the coastal part of northern Philippines, while the province of Bukidnon is in the very southern part of the country, the disparate geographic locations may have contributed to the differences in yields. Results from the ordered probit baseline model on insurance choice indicate that in the full sample, farmers from Pangasinan are 5% more likely to choose basic insurance and 10% more likely to choose multi-risk insurance than farmers in Bukidnon. Similar results are found in the insured subsample.[14] Insured farmers in Pangasinan are 6% more likely to choose basic cover and 22% more likely to choose multi-risk cover. Pangasinan is a province that is susceptible to weather shocks because it has two distinct seasons. As for the other two provinces, Bukidnon's wet and dry seasons are not very distinct, and Isabela has rainfall that is evenly distributed throughout the entire year. In addition, Pangasinan was hit by massive flooding due to Tyhoon Ketasana in October 2009 and

[14] Note that even in the insured subsample, there are some farmers with $Insurance_i = 0$ so that an ordered probit model can be estimated. This is because as we explained above, we set $Insurance_i = 0$ for those farmers who bought insurance but stated that they would not purchase insurance if not required by their lenders.

then again by Tyhoon Falcon in 2010. This shows that Pangasinan is more vulnerable to weather risks and thus, farmers may prefer more coverage.

Results from the main regressions where the vector X_i is included together with the risk classification variables are reported in Tables 1.4 and 1.5. We first discuss Table 1.4, the full sample results. Several findings are worth mentioning. First, several factors are found to have a statistically significant effect on yield. Farms with higher historical yields have higher yield in the current year. For every one thousand kilogram increase in historical yield, yield in 2012 increases by one half thousand kilograms. As discussed above, historical yield performance accounts for the heterogeneity in farming ability/conditions which are not captured by the location dummies. Farmers with superior farming ability, better land quality, more favorable temperature and soil moisture levels would have consistently higher yields per hectare as compared to their peers in the same province.

Farmers who follow instructions when applying chemicals to their fields are found to produce 632 kilograms more corn per hectare than those who do not read labels. These farmers follow the best advice, resulting in better yields. An interesting finding is that farmers that used hybrid seed varieties tend to produce one thousand kilograms more than those who used GMO/Bt corn varieties. However, GMO/Bt seeds are generally believed to guarantee higher yields and be more resistant to various risks. To reconcile this with our findings, we conjecture that the potential yield advantage of GMO/Bt seeds over hybrids is more evident when there is high pest pressure. But as mentioned earlier (see p. 11 above), the incidence of pest losses during the survey year is low and in this

case (i.e., under a year with more “normal” pest conditions) our survey data indicate that hybrid seed varieties tend to have higher yields than GMO/Bt seed varieties. In addition, it may also be possible that farmers in the study areas still do not have enough experience with the GMO/Bt corn and hence theymay be less productive when using GMO/Bt seeds. If this is the case, then they need more technical assistance and guidance.

Farmers with land ownership produce on average one half thousand kilograms per hectare less than farmers without land ownership. These farmers probably have less incentive to work hard as they do not need to pay cash or crop rent. It is also possible that a full owner adopts a more long-term view towards his lands so he does not want to exploit too much from the soil productivity in just one year. Besides, farmers who plant other crops besides corn are found to have lower corn yield as well, probably due to decreasing returns to scope.

Second, we also have some interesting findings from the insurance choice regression. If a farmer can recall one more word, he is 0.8% more likely to purchase the basic natural disaster insurance and 1.5% more likely to purchase the multi-risk cover insurance. Farmers with higher cognitive ability better understand the importance of crop insurance as a risk management tool and how insurance works and hence are more likely to purchase insurance. Farmers who use hybrid seeds are more likely to purchase insurance than farmers who use GMO/Bt seeds. They are 3.3% more likely to purchase basic cover and 6% more likely to purchase multi-risk cover. Since GMO/Bt corn are more resistant to pests anddiseases, farmers who adopt these varieties may think that production risks (in general) have already been minimized by using these new seed

varieties and they no longer need crop insurance (i.e., crop insurance and GMO/Bt are substitutes). On the other hand, those farmers who stick to hybrid seeds perceive that they face more risks and they purchase insurance as a protection.

Organization membership is related to higher demand of insurance. Organization members are 7.5% and 13.7% more likely to choose basic and multi-risk insurance, respectively. 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. The total area of planted fields is negatively correlated with insurance demand. For one hectare increase in area of planted fields, farmers are 0.8% and 1.5% less likely to purchase basic and multi-risk coverage, respectively. This is consistent with our Corollary 2 above that wealthier farmers demand less insurance. Finally, as expected, farmers who borrow more demand more insurance.

The estimates from regressions using the insured subsample are reported in Table 1.5. The results are very similar to those using the full sample, both in terms of estimates and statistical significance, with a few exceptions. First, reading instruction labels no longer has a statistically significant effect on yield. Second, the amount of loan, being an organization member and total area of planted fields no longer have a statistically significant effect on insurance demand.

In summary, our analysis identifies using hybrid seeds as a source of advantageous selection into the corn crop insurance plan sold by PCIC. Those farmers who use hybrid seeds tend to have higher yields because: (i) the pest pressure during the

2012 survey year is low (and the yield advantage of the new genetically modified varieties are less likely to observed when pest pressure is low) or any other one single year weather shock, and/or (ii) farmers in the Philippines still have not had adequate experience to efficiently manage GMO/Bt corn. At the same time, these farmers purchase more insurance because they are more cautious, as indicated by their lower willingness to try the relatively new but uncertain GMO/Bt seeds. As a result, if more farmers using hybrid seeds enroll in the program, the overall risk decreases. In addition, the estimate for the correlation coefficient of error terms from the two equations, ρ, is -0.23 for the full sample and -0.21 for the subsample, both of which are statistically significant. This implies the residuals from the two equations are negatively correlated. Thus, there are unobserved variables that are positively correlated with insurance demand but negatively correlated yield performance. These are the unidentified sources of adverse selection.

Robustness Check

One concern is that the variable $Credit_i$ may cause endogeneity problem. For example, if a farmer got a lottery in one year and then he would not borrow and also not buy insurance. To address this concern, one robustness check is conducted by dropping the $Credit_i$ variable in the insurance demand equation. The results for the full sample and insured sample are reported in Table 1.7 and 1.8 respectively. The estimation produces almost identical results as the main ones in terms of both significance and magnitude. Therefore, the possible bias resulted from the endogeneity problem associated with $Credit_i$ is negligible.

Conclusions

Using data from a survey of 426 corn farmers in the Philippines, we examine the existence and identify the sources of advantageous selection in crop insurance. Our results suggest that using hybrid seeds instead of genetically modified seeds is a source of advantageous selection in this market. We also find that farmers with higher historical yield, without land ownership and who specialize in corn production are more productive and farmers with higher cognitive ability, being a member of an organization and lower wealth purchase more insurance coverage.

Because crop insurance serves as both a risk management tool for the farmers as well as a hedge against credit risk for the lending institutions in the Philippines, this program is critically important for improving farmer welfare and ensuring food security. However, the participation rate has been low. One possible reason is that the premiums are too high. Currently, crop insurance premiums only vary by province in the Philippines. Our results suggest that PCIC should adopt a more complex procedure for premium determination. Discounts could be offered to farmers who use hybrid seeds, with higher historical yield, without land ownership and who specialize in corn production. With discounts, more farmers of these types will enroll in the program. And as these farmers are shown to be productive, this will only improve the financial balance sheet of the program.

Our result that historical yield is a major determinant of current yield also suggests a possible way to reduce moral hazard behavior by the farmers. The PCIC could offer premiums discounts for farmers with high historical yield. This provides incentives

to farmers to improve their current yield so that they can get premium discounts in the future. In fact, some efforts in this direction have already been made. Some subsidized insurance programs in the Philippines offer no-claim benefit or reduction in premium rates if famers pay debt on time (Reyes, Gloria and Mina, 2015).

One caveat readers should bear in mind when interpreting our results is that we do not consider and correct the potential endogeneity of some of the variables in our regressions due to lack of data on appropriate instrumental variables. Variables that describe short-run decisions are the ones most likely to be endogenous. In our context, these include the hybrid seeds variable and the specialization variables. If certain unobserved farmer/farm characteristics influence farmers' decisions regarding insurance purchase and seed use and specialization at the same time, the seed use and specialization variables will be endogenous and our estimates will be biased. We do not believe this is likely to be the scenario in our case because we have included the historical yield variable in the regressions. If the unobserved farmer/farm characteristics that cause the endogeneity problem are time invariant or are highly correlated over time, then these unobserved factors would be subsumed by the historical yield variable and our analysis would not suffer from the endogeneity problem.

REFERENCES

Cawley, J., and T. Philipson. 1999. “An Empirical Examination of Information Barriers to Trade in Insurance.” *American Economic Review* 89: 827-846.

Chiappori, P., and B. Salanie. 2000. “Testing for Asymmetric Information in Insurance Markets.” *Journal of Political Economy* 108 (1): 56-78

Davidoff, T., and G. Welke. 2005. “Selection and Moral Hazard in the Reverse Mortgage Market.” Working paper, Haas School of Business, University of California, Berkeley.

De Meza, D., and D. C. Webb, 2001. “Advantageous Selection in Insurance Markets.” *RAND Journal of Economics* 32 (2): 249-262.

Dionne, G., C. Gourieroux, and C. Vanasse. 1998. “Evidence of Adverse Selection in Automobile Insurance Markets.” In G. Dionne and C. Laberge-Nadeu, eds. *Automobile Insurance: Road Safety, New Drivers, Risks, Insurance Fraud, and Regulation.* Boston: Kluwer Academic Press, pp. 13-46.

Dionne, G., C. Gouriéroux, and C. Vanasse. 2001. “Testing for evidence of adverse selection in the automobile insurance market: A comment.” *Journal of Political Economy* 109(2): 444-453.

Fang, H., M. P. Keane, and D. Silverman. 2008. “Sources of Advantageous Selection: Evidence from the Medigap Insurance Market.” *Journal of Political Economy* 116(2): 303-348.

Finkelstein, A. and K. McGarry. 2006. “Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market.” *The American Economic Review* 96 (4) : 938-958.

Garrido, C. A., and D. Zilberman. 2007. “Revisiting the demand of agricultural insurance: the case of Spain.” *Agricultural Finance Review*: 43-66.

Goodwin, B. 1993. "An Empirical Analysis of the Demand for Multiple Peril Crop Insurance." *American Journal of Agricultural Economics* 75: 425-434.

Hou, L., D. L. Hoag, and Y. Mu. 2011. “Testing for adverse selection of crop insurance in northern China.” *China Agricultural Economic Review* 3(4): 462-475.

Just, R. E., L. Calvin, and J. Quiggin. 1999. “Adverse selection in crop insurance: Actuarial and asymmetric information incentives.” *American Journal of Agricultural Economics* 81(4): 834-849.

Knight, T. O., and K. H. Coble. 1997. “Survey of US multiple peril crop insurance literature since 1980.” *Review of Agricultural Economics* 19(1): 128-156.

Makki, S. S., and A. Somwaru. 2001. "Evidence of Adverse Selection in Crop Insurance Markets." *Journal of Risk and Insurance* 68 (4): 685-708.

Quiggin, J., G. Karagiannis, and J. Stanton. 1993. "Crop Insurance and Crop Production: An Empirical Analysis Study of Moral Hazard and Adverse Selection." *Australian Journal of Agricultural Economics* 37 (2): 95-113.

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. T*argeting the Agricultural Poor: The Case of PCICs Special Programs*. Makati, Philippines: Philippine Institute for Development Studies, No. DP 2015-08, January.

Roberts, M. J., N. Key, and E. O'Donoghue. 2006. “Estimating the extent of moral hazard in crop insurance using administrative data.” *Review of Agricultural Economics*: 381-390.

Rothschild, M., and J. Stiglitz. 1976. “Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information.” *The Quarterly Journal of Economics* 90(4): 629-649.

Smith, V. H., and A. E. Baquet. 1996. “The demand for multiple peril crop insurance: evidence from Montana wheat farms.” *American journal of agricultural economics* 78(1): 189-201.

Smith, V. H., and B. K. Goodwin. 1996. “Crop insurance, moral hazard, and agricultural chemical use.” *American Journal of Agricultural Economics* 78(2): 428-438.

Yorobe, Jr. J. M., and P. M. Luis. 2015. *Improving the Agricultural Insurance Program to Enhance Resilience to Climate Change: Evidence from Corn Production in the Philippines.* Laguna, Philippines: Southeast Asian Regional Center for Graduate Study and Research in Agriculture, Technical report, January.

Table 1.1 List of Variables

Variable	**Unit**	**Definition**
Dependent variables		
Yield	1000 kg/hectare	Yield of the largest parcel per hectare in 2012
Insurance		=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		
HistoricalYield	1000 kg/hectare	Mean yield of the largest parcel per hectare of 2010 and 2011
Safety		=1 if farmer doesn't use bare hands to handle chemicals and 0 otherwise
Label		=1 if farmer reads the labels before using chemicals, 0 otherwise
Cognitive	Number of words	Number of words recalled from 20 words by the farmers
Credit	10,000PHP	Total amount of loan
Hybrid		=1 if hybrid varieties and 0 otherwise
DistanceRoad	Km	Distance to nearest market
DistanceExt	Km	Distance to extension office
Org		=1 if a member in any organization and 0 otherwise
FullOwner		=1 if full owner and 0 other tenure types
PartOwner		=1 if partial owner and 0 other tenure types
Area	Hectare	Total area of planted field
Experience	Number of years	Years in corn farming
OtherCrop		=1 if farmer plants other crops aside from corn and 0 otherwise
Livestock		=1 farmer raises any livestock and 0 otherwise
Isabella		=1 if in Isabela and 0 otherwise
Pangasinan		=1 if Pangasinan and 0 otherwise

Table 1.2 Summary Statistics

	Full Sample					Non-insured					Insured					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Diff. in Means**
Yield	399	5.6431	2.9456	0	15	200	5.5221	2.8494	0.4	14.5455	199	5.7647	3.0416	0	15	-0.24
Insurance	396	0.3384	0.6763	0	2						196	0.6837	0.8302	0	2	
HistoricalYield	383	5.0957	2.4663	0	18	189	4.8911	2.5248	0.5333	18	194	5.2949	2.3977	0	12.65	-0.4
Safety	399	0.4211	0.4943	0	1	200	0.4250	0.4956	0	1	199	0.4171	0.4943	0	1	0.01
Label	397	0.9093	0.2875	0	1	200	0.9150	0.2796	0	1	197	0.9036	0.2960	0	1	0.01
Cognitive	398	7.2613	3.4308	0	20	199	6.8141	3.0962	0	16	199	7.7085	3.6894	1	20	-0.89***
Credit	398	3.0581	3.6640	0	34.5	200	1.7848	2.7733	0	16	198	4.3444	3.9970	0	34.5	-2.56***
Hybrid	399	0.7093	0.4547	0	1	200	0.7050	0.4572	0	1	199	0.7136	0.4532	0	1	-0.01
DistanceRoad	389	0.9466	1.8339	0.0001	20	197	0.7750	1.2622	0.0001	6	192	1.1227	2.2661	0.001	20	-0.35*
DistanceExt	365	12.6102	10.5813	0	50	185	13.2272	10.7986	0	50	180	11.9761	10.3450	0	38	1.25
Org	399	0.4962	0.5006	0	1	200	0.3450	0.4766	0	1	199	0.6482	0.4787	0	1	-0.3***
FullOwner	369	0.5881	0.4928	0	1	198	0.6111	0.4887	0	1	171	0.5614	0.4977	0	1	0.05
PartOwner	369	0.1057	0.3079	0	1	198	0.0909	0.2882	0	1	171	0.1228	0.3292	0	1	-0.04
Area	392	2.4981	2.3378	0.25	26	197	2.4019	2.2735	0.25	14.4	195	2.5953	2.4029	0.25	26	-0.19
Experience	397	15.0403	8.5101	1	54	200	15.3550	8.9172	1	54	197	14.7208	8.0862	1	36	0.63
OtherCrop	399	0.5388	0.4991	0	1	200	0.5500	0.4987	0	1	199	0.5276	0.5005	0	1	0.02
Livestock	399	0.1529	0.3603	0	1	200	0.1300	0.3371	0	1	199	0.1759	0.3817	0	1	-0.05

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 1.3 Baseline Regression Results

	Yield		***Insurance***					
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Marginal Effects on Probability of Choosing Basic Insurance**	**Std. Err.**	**Marginal Effects on Probability of Choosing Multi-risk Insurance**	**Std. Err.**
Panel A: Full sample								
Isabella	2.4104***	0.28	0.0754	0.18	0.0075	0.02	0.0143	0.03
Pangasinan	4.4120***	0.29	0.5442***	0.17	0.0542***	0.02	0.1033***	0.03
_cons	3.3730	0.20						
ρ	-0.0317	0.07						
N of obs.	399							
Stat.	Adjusted R2 = 0.3686		Pseudo R2 = 0.0236					
Panel B: Insured sample								
Isabella	2.8633***	0.42	0.0606	0.21	0.0051	0.02	0.0174	0.06
Pangasinan	4.4924***	0.42	0.7621***	0.21	0.0643***	0.02	0.2195***	0.06
_cons	3.3025	0.30						
ρ	-0.0796	0.09						
N of obs.	199							
Stat.	Adjusted R2= 0.3686		Pseudo R2= 0.0435					

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 1.4 Main Regression Results for the Full Sample

	Yield		***Insurance***					
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Marginal Effects on Probability of Choosing Basic Insurance**	**Std. Err.**	**Marginal Effects on Probability of Choosing Multi-risk Insurance**	**Std. Err.**
HistoricalYield	0.5536***	0.05	0.0178	0.04	0.0015	0.00	0.0028	0.01
Safety	0.0199	0.21	-0.0682	0.18	-0.0058	0.02	-0.0107	0.03
Label	0.6324*	0.37	-0.1944	0.29	-0.0165	0.02	-0.0304	0.05
Cognitive	-0.0311	0.03	0.0929***	0.03	0.0079***	0.00	0.0145***	0.00
Hybrid	0.9948***	0.23	0.3839*	0.20	0.0325*	0.02	0.0600*	0.03
DistanceRoad	-0.0228	0.05	0.0291	0.04	0.0025	0.00	0.0045	0.01
DistanceExt	-0.0036	0.01	0.0012	0.01	0.0001	0.00	0.0002	0.00
Credit			0.0661***	0.02	0.0056***	0.00	0.0103***	0.00
Org	0.0055	0.22	0.8792***	0.20	0.0745***	0.02	0.1374***	0.03
FullOwner	-0.4216***	0.23	-0.1214	0.19	-0.0103	0.02	-0.0190	0.03
PartOwner	0.0220	0.35	0.0030	0.28	0.0003	0.02	0.0005	0.04
Area	0.0310	0.05	-0.0965*	0.05	-0.0082*	0.00	-0.0151*	0.01
Experience	-0.0053	0.01	-0.0093	0.01	-0.0008	0.00	-0.0015	0.00
OtherCrop	-0.4449*	0.25	0.1174	0.22	0.0099	0.02	0.0184	0.04
Livestock	0.1501	0.28	-0.2101	0.24	-0.0178	0.02	-0.0328	0.04
Isabella	2.0002***	0.30	0.6581***	0.26	0.0558***	0.02	0.1029***	0.04
Pangasinan	3.1740***	0.34	0.9975***	0.30	0.0845***	0.03	0.1559***	0.05
_cons	0.6086	0.69						
ρ	-0.2345***	0.09						
N of obs.	313							
Stat.	Adjusted R2 = 0.6036		Pseudo R2=0.1717					

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 1.5 Main Regression Results for the Insured Subsample

	Yield		***Insurance***					
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Marginal Effects on Probability of Choosing Basic Insurance**	**Std. Err.**	**Marginal Effects on Probability of Choosing Multi-risk Insurance**	**Std. Err.**
HistoricalYield	0.5144***	0.07	0.0005	0.05	0.0000	0.00	0.0001	0.01
Safety	0.0862	0.33	0.0023	0.24	0.0001	0.01	0.0006	0.06
Label	0.6186	0.57	-0.1416	0.38	-0.0087	0.02	-0.0368	0.10
Cognitive	-0.0156	0.05	0.1177***	0.04	0.0073***	0.00	0.0306***	0.01
Hybrid	0.8708**	0.37	0.5707**	0.27	0.0352*	0.02	0.1483**	0.07
DistanceRoad	-0.0074	0.06	0.0360	0.05	0.0022	0.00	0.0093	0.01
DistanceExt	-0.0031	0.02	0.0017	0.01	0.0001	0.00	0.0004	0.00
Credit			0.0190	0.03	0.0012	0.00	0.0049	0.01
Org	0.1131	0.39	0.2743	0.29	0.0169	0.02	0.0713	0.07
FullOwner	-0.6783**	0.33	-0.0021	0.24	-0.0001	0.01	-0.0005	0.06
PartOwner	-0.3876	0.50	0.0670	0.35	0.0041	0.02	0.0174	0.09
Area	-0.0493	0.07	-0.1013	0.07	-0.0063	0.00	-0.0263	0.02
Experience	0.0042	0.02	0.0027	0.01	0.0002	0.00	0.0007	0.00
OtherCrop	-0.7981**	0.40	0.4154	0.30	0.0256	0.02	0.1079	0.08
Livestock	0.0843	0.41	-0.3049	0.30	-0.0188	0.02	-0.0792	0.08
Isabella	2.0874***	0.47	0.9988***	0.34	0.0617***	0.02	0.2595***	0.08
Pangasinan	3.4610***	0.52	1.3056***	0.38	0.0806***	0.03	0.3392***	0.09
_cons	0.9060	1.04						
ρ	-0.2094*	0.10						
N of obs.	143							
Stat.	Adjusted R2= 0.6047		Pseudo R2= 0.1484					

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 1.6 Robustness Check for Full Sample (dropping the *Credit* variable)

	Yield		***Insurance demand***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
TwoyearMeanYield	0.5536***	0.05	0.0252	0.04
Safety	0.0199	0.21	-0.1174	0.18
Cautiousness	0.6324*	0.37	-0.1961	0.29
Cognitive	-0.0311	0.03	0.0950***	0.03
HybridSeed	0.9948***	0.23	0.4779***	0.20
DistanceRoad	-0.0228	0.05	0.0348	0.04
DistanceExt	-0.0036**	0.01	0.0036	0.01
Org	0.0055	0.22	0.9133***	0.19
FullOwner	-0.4216	0.23	-0.1621	0.19
PartOwner	0.0220	0.35	-0.0062	0.28
AreaTot	0.0310	0.05	-0.0489	0.04
YearinCorn	-0.0053	0.01	-0.0076	0.01
OtherCrop	-0.4449**	0.25	0.0350	0.22
Livestock	0.1501	0.28	-0.1839	0.24
Isabella	2.0002***	0.30	0.8042***	0.25
Pangasinan	3.1740***	0.34	1.0801***	0.29
_cons	0.6086	0.69		
ρ	-0.2182***	0.09		
N of obs.	313		312	
Stat.	Adjusted R2= 0.6036		Pseudo R2= 0.1484	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 1.7 Robustness Check for Insured Sample (dropping the *Credit* variable)

	Yield		***Insurance demand***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
TwoyearMeanYield	0.5119***	0.08	0.0017	0.05
Safety	0.0663	0.33	-0.0051	0.23
Cautiousness	0.5987	0.58	-0.1328	0.38
Cognitive	-0.0153	0.05	0.1180***	0.04
HybridSeed	0.8673**	0.38	0.6199***	0.27
DistanceRoad	-0.0074	0.06	0.0342	0.05
DistanceExt	-0.0052	0.02	0.0038	0.01
Org	0.1535	0.40	0.2710	0.29
FullOwner	-0.7112**	0.34	-0.0060	0.24
PartOwner	-0.3844	0.51	0.0541	0.35
AreaTot	-0.0528	0.07	-0.0821	0.06
YearinCorn	0.0043	0.02	0.0031	0.01
OtherCrop	-0.7681**	0.41	0.3739	0.29
Livestock	0.0978	0.41	-0.3040	0.31
Isabella	2.1233***	0.47	1.0058***	0.33
Pangasinan	3.4353***	0.52	1.3200***	0.38
_cons	0.9343	1.06		
ρ	-0.2022**	0.11		
N of obs.	140		140	
Stat.	Adjusted R2= 0.5931		Pseudo R2= 0.1449	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Chapter 2 Estimating the Effect of Crop Insurance on Input Use when Insured Farmers are Monitored

Introduction

Agriculture plays a crucial role in economic stability and growth. Not only does it provide necessities to people, such as food and clothes, it also produces raw materials for production in other sectors. Being at such a strategically important place, it is in the public interest to have a stable agricultural sector that protects food security and supports the economy. These are the reasons that many crop insurance programs have been introduced across the world since the last century. Crop insurance programs are mainly established by governments as a risk management tool for farmers. It aims at providing financial stability that allows farmers to recover from natural disasters or other disastrous events, and offering farmers the confidence to make investment in production technology that boosts future growth. As insurance reduces downside risks and increases expected return to investment, farmers with insurance will invest more in production and use more inputs.

However, implementing the crop insurance programs in a sustainable and effective way is challenging. Once farmers get insured, they game the system to their advantage. One problem is moral hazard. As insured farmers will be compensated if they have losses, they tend to exert less effort during production (i.e. use less input). Smith and Goodwin (1996) showed that insurance purchase made farmers use fewer chemical inputs based on a survey of Kansas dryland wheat farmers in 1992. Babcock, and Hennessy (1996) pointed out that nitrogen fertilizer and insurance are substitutes, so farmers under insurance coverage are likely to use less nitrogen. Quiggin, Karagiannis and Stanton (1993) found negative but insignificant effect of insurance on input use. Goodwin, Vandeveer, and Deal (2004) showed that in the Upper Great Plains, the rising in adoption of insurance came with a decrease in fertilizer and chemical expenditures by wheat and barley farmers.[15]

Some strategies have been proposed and implemented to fight against moral hazard. One strategy is to base premiums on past performance. In the U.S. crop insurance markets, as pointed out by Weber, Key, and O'Donoghue (2015), the potential effect of moral hazard is restrained by the structure of insurance contract that sets premiums and guarantee yields based on yield histories. A claim in one year increases the premium and decreases the guaranteed yield levels for the following years. For another example, Dionne et al. (2005) showed that a change in auto insurance regulation that increased the

[15] There is also evidence suggesting that crop insurance has no or positive effect on input use. For instance, Horowitz and Lichtenberg (1993) showed that in ten states of the US, crop insurance had a positive effect on input use for corn producers. Wu (1999) examined the effect of crop insurance on crop mix and chemical use in the Central Nebraska Basin, and showed that insurance shifted land from hay and pasture to corn and increased the total chemical use. A recent study by Weber, Key, and O'Donoghue (2015) studied the effect of insurance on farm specialization and chemical use. They found that insurance decreased the share of acres harvested but had little effects on input use.

premiums charged to drivers with worse records reduced accidents. The second strategy is to increase the co-pay rates. As people's share of losses increases, they are motivated to not engage in risky behaviors. For example, Chiappori, Durand, and Geoffard (1998) studied a change in French health insurance from a full coverage to a ten percent copayment, and showed that the copayment decreased doctor home visits. Yet another strategy is monitoring. As moral hazard arises because of hidden actions, if insurers can monitor insureds' behaviors, the moral hazard problem can be curbed. Bellemare (2010) showed that, for a sample of contract farmers in Madagascar, the number of visits by agricultural technicians had a positive and statistically significant effect on production. Frisvold (1994) showed that supervision needs to be employed to increase hired labor productivity based on data from an Indian village. Jacoby and Mansuri (2009) found that yields on the plots cultivated by supervised tenants were significantly higher than those cultivated by unsupervised tenants.

This paper aims to study the effectiveness of monitoring as a mechanism to fight against moral hazard in crop insurance markets. Monitoring is a unique feature of the Philippines crop insurance program. In the Philippines, borrowed farmers are required to purchase insurance as collateral and they are monitored by bank technicians during the growing season to ensure that the loans are not diverted for other purposes. Self-financed farmers are also required to accept supervision from agricultural technicians from the Philippines Crop Insurance Incorporation (PCIC) if they would like to participate in the crop insurance program. As a result, all insured farmers are monitored by technicians during the growing season.

Lacking data on monitoring such as the number of visits technicians paid to the farmers during the growing season, we cannot test the effect of monitoring on moral hazard behaviors by the farmers directly. Instead, we first propose a theoretical model that takes into account several features of the Philippines crop insurance program and show that when insured farmers are being monitored and if the monitoring is effective in curbing moral hazard behavior, insured farmers will use more of certain inputs than uninsured farmers. In the empirical section, we test this hypothesis using a survey dataset of corn farmers in the Philippines. Our results show that insured farmers indeed use more fertilizers, weedicides as well as spend more on chemicals in total. Therefore, we conclude that monitoring is an effective way to curb moral hazard behavior in crop insurance programs.

The remaining of the paper is organized as follows. The next section introduces the Philippines crop insurance program. The third section lays out our theoretical framework and derives our main testable hypothesis. Our data is described in section four and section five details the estimation strategy. The sixth section discusses the empirical results and the final section concludes.

Background

The agricultural industry has been recognized by the Philippine 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), weather shock is the major factor that contributes to impoverishment in the Philippines. Farmers could mitigate the impact of weather shock 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 suitable during recent years when farmers have been confronted with new 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. 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).[16] 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

[16] 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.

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.[17]

Farmers can purchase insurance through several different venues, such as lending institutions where they obtain their loans, the PCIC regional office or other PCIC authorized underwriting agents. Farmers who want to get insured have to submit application before the fifteenth day after planting. 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. However, it should be noted that the PCIC corn insurance product is subject to the following liability ceilings: (a) PHP 40,000/USD 948[18] per hectare for hybrid and GMO corn varieties, and (2) PHP 28,000/USD 664 per hectare for open-pollinated varieties.

Reyes et al. (2015) points 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

[17] 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.
[18] The average 2012 exchange rate was 0.023 USD/PHP.

vs. multi-risk), and cropping 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) 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.

The Philippine government heavily subsidizes corn insurance premiums. The government pays more than 50% of the total insurance premium for corn. Lending institutions also share a portion of the premium if the insured farmer borrows from them (i.e., the borrower client). Therefore, the borrower clients' premiums are shared among the lending institution, the government, and the farmers themselves. The self-financed clients' premiums, on the other hand, are only shared with the government. But note that the total premium rate is typically the same for both the borrowing and the self-financed farmers.[19] In addition, the government's share is also the same for both types of farmers. This arrangement means that self-financed clients have to pay an additional amount of premium (relative to the borrower clients), which is equivalent to what would have been assumed by lending institutions if they were borrower clients.

The premium rate shared by the lending institution and the government is also constant across different types of insurance cover (i.e., natural disaster vs. multi-risk) as

[19] See the PCIC table of national composite premium rates and premium sharing schemes of the corn insurance program at: http://pcic.gov.ph/index.php/insurance-packages/corn-crop-insurance/.

well as different risk classifications (i.e., low vs. medium vs. high). This scheme implies that the premium rate paid by the lending institutions and the government remains the same for farmers with different risk classification levels and the additional premium for being high risk will have to be borne by the high-risk farmer themselves. For example, the premium rate (premium as a percentage of liability) paid by a self-financed corn farmer classified as high risk is 11.48% and the government pays 10.62%; while a low risk farmer only pays 5.83% himself with the government still paying 10.62%.

One important and unique feature of the Philippine crop insurance program is that during production, insured farmers are monitored by technicians. Farmers who borrow money from formal sources such as banks are required to purchase insurance. Furthermore, the approval and the amount of the loan are based on the stated Farm Plan and Budget they submit. Once the loan is issued, the bank technicians monitor farmers' behavior during the growing season to make sure the loan is not diverted for other purposes and used to purchase inputs according to the stated plan. For those farmers who do not borrow from formal sources, as mentioned above, they also need to submit the Farm Plan and Budget to PCIC as part of their insurance application package. These farmers are allowed to purchase insurance only if they agree to place themselves under the technical supervision of PCIC-accredited agricultural production technicians during the growing season. Therefore, for both types of insured farmers, their farming activities are monitored by technicians during the production season and there is little room for them to engage in moral hazard behavior such as using less amount of inputs than what they state in the Farm Plan and Budget.

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% 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).

From 1982 to 1990, the PCIC corn insurance program had a difficult time when the total claim amount consistently exceeded total premium collected. Since 1990, the situation has been reversed and total premiums are now much larger than the indemnities paid. In 2012, the total premium was two times larger than the total indemnities paid out to producers. In addition, the number of insured farmers had declined from the peak at 40,410 in 1990 to 3,910 in 2007. However, after 2007, the number of insured farmers has steadily increased and reached 12,271 in 2012. This growth in participation may be attributed to the increased frequency of natural disasters during that period. As a result, farmers may have had an increasing awareness of the importance of insurance. This growth in participation may also be ascribed to the promotion of various new largely-subsidized special crop insurance programs during this period. These special programs were officially launched in 2012 (Reyes, Gloria and Mina, 2015).

In 2012, 29% of the insured farmers had indemnities paid from the PCIC corn crop insurance program. As for the causes of loss, typhoons, floods and droughts were the main causes. For example, in 2012, an indemnity of PHP 15.77/USD 0.374 million was paid for losses due to typhoons or floods, while PHP 4.53/USD0.107 million and PHP 6/USD 0.142 million were paid for losses due to pests and diseases, respectively. In

general, the losses caused by natural disasters are more than twice the losses caused by pests or diseases (Yorobe and Luis, 2015).Therefore, seasonal climate variability and occurrence of adverse weather events are the main sources of uncertainty for corn farmers in the Philippines.

Model

In this section, we propose a theoretical model that takes into account many of the features of the Philippines crop insurance program, and predict the relationship between insurance and input use when the insured farmers are monitored by technicians from the insurance agency during the production season. Formally, assume a representative farmer owns one hectare of arable land.[20] The production function for the farmer takes the form of $f(x)$ with $f' > 0$ and $f'' < 0$, where x denotes the inputs used. The farmer has a ρ $(0 < \rho < 1)$ chance of encountering a risk event during the production season that will reduce his harvest from $f(x)$ to $\theta(x)f(x)$, where $0 < \theta < 1$ and $\theta'(x) > 0$. Due to its geographical characteristics, the Philippines is prone to natural calamities such as typhoons, floods and volcanic eruptions. Thus, farming decisions have little impact on the chance for these disasters to happen. Also, farms in the Philippines are usually small and hence the outbreak of pest infestation is mainly influenced by factors uncontrollable to the farmers, as plant pests and disease infestation usually occur in epidemic proportion. For these reasons, we assume that the chance for a disaster to happen, ρ, is exogenous to

[20] We fix the size of the land to focus our analysis on the effect of insurance on the intensive margin of input use.

the farmer. On the other hand, the amount of yield loss when a disaster happens can be affected by the amount of inputs used. For instance, fertilizers increase plant vigor and vitality so its natural capacity to combat pests and diseases improves. Moreover, both herbicides and pesticides decrease potential yield damage from pests. Therefore, we allow θ to be an increasing function of x in our model.

The farmer is risk averse. His preference is characterized by the utility function $U(I) = -I^{-1}$ if $I > 0$ and $U(I) = -\infty$ if $I \leq 0$, where I is wealth. This is the power utility function with the constant relative risk aversion parameter being 2.[21] Without insurance, the farmer's objective is to maximize the following expected utility function,

$$EU = (1-\rho)U[f(x) - wx + Y] + \rho U[\theta(x)f(x) - wx + Y], \tag{1}$$

where Y is the initial wealth of the farmer, w is the unit input price and the price of output is normalized to be one. In (1), the first part represents the case where no disaster happens and the second part represents the case where a disaster causes a loss in yield. The optimal solution to farmer's maximization problem (1) is denoted as x^*.

The farmer can participate in the Philippines corn crop insurance program. If the farmer purchases the crop insurance, he will need to submit a farming plan to the insurance agency, detailing the amount of inputs he plans to use. Then, the insurance agency will assign a technician to monitor his farming practices during the production season, making sure the farmer follows what he commits in the plan. As a result, there is no opportunity for the farmer to engage in moral hazard behavior by using less inputs than what he put down in the farming plan. When a disaster hits, the farmer will be

[21] We use this specific utility function for the purpose of simplifying our proof below.

reimbursed for the input costs in proportion to his loss in yield. Therefore, in this case, the farmer's objective function becomes,

(2) $$EU = (1-\rho)U[f(x) - wx + Y] + \rho U[\theta(x)f(x) - \theta(x)wx + Y].$$

Equation (2) differs from (1) only in the second part.[22] When a disaster hits and $[1 - \theta(x)]$ of the yield is lost, the farmer will be reimbursed for the same proportion of his input cost, reducing the cost from wx to $\theta(x)wx$. The optimal solution to farmer's maximization problem (2) is denoted as x_I^*.

Furthermore, we consider two cases. Under the first case, we assume that the marginal effect of input on yield is larger when there is no disaster than when a disaster hits, that is,[23]

(3) $$f'(x) > [\theta(x)f(x)]' = \theta'(x)f(x) + \theta(x)f'(x).$$

This assumption is more likely to hold for inputs that are for yield-enhancing, such as fertilizers, instead of damage-control inputs. Now we are ready to state the following theorem,

Theorem: Under the assumptions made above, $x_I^* > x^*$.

Proof: By definition, x^* is the solution to the first order condition of the expected utility maximization problem (1),

(4) $$(1-\rho)\frac{f'(x^*)-w}{[f(x^*)-wx^*+Y]^2} + \rho\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2} = 0.$$

Similarly, x_I^* is the solution to the first order condition of the expected utility maximization problem (2),

[22] Premium is considered as a sunk cost and not included in the insurance model. It is because we do not model insurance purchase decision and only focus on the second stage of input use decision.

[23] For example, if $\theta(x) = \frac{1-e^{-x}}{2}$ and $f(x) = M(1-e^{-x})$, then (3) holds.

(5) $$(1-\rho)\frac{f'(x_I^*)-w}{[f(x_I^*)-wx_I^*+Y]^2}+\rho\frac{\theta'(x_I^*)f\quad(x_I^*)+\theta(x_I^*)f'(x_I^*)-\theta(x_I^*)w-\theta'(x_I^*)wx^*}{[\theta(x_I^*)f(x_I^*)-\theta(x_I^*)wx_I^*+Y]^2}=0.$$

Replacing x_I^* with x^* in the left hand side of (5) and using (4) give us,

(6) $$(1-\rho)\frac{f'(x^*)-w}{[f(x^*)-wx^*+Y]^2}+\rho\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}-$$

$$\rho\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}+\rho\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-\theta(x^*)w-\theta'(x^*)wx^*}{[\theta(x^*)f(x^*)-\theta(x^*)wx^*+Y]^2}=$$

$$\rho\left\{\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-\theta(x^*)wx^*+Y]^2}-\frac{\theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}\right\}+$$

$$\rho\frac{[1-\theta(x^*)]w-\theta'(x^*)wx^*}{[\theta(x^*)f(x^*)-\theta(x^*)wx^*+Y]^2}.$$

To examine whether (6) is positive or negative, we first note that (3) and (4) imply that,

(7) $$f'(x^*)-w>0 \text{ and } \theta'(x^*)f(x^*)+\theta(x^*)f'(x^*)-w<0.$$

With (7), it is clear that the first part of (6) (the term inside the bracket) is positive because the two terms inside the bracket share the same negative numerator and the denominator of the first term is larger than that of the second term. The second term of (6) is also positive because

(8) $$[1-\theta(x^*)]w-\theta'(x^*)wx^*>w-\theta(x^*)f'(x^*)-\theta'(x^*)wx^*>w-$$

$$\theta(x^*)f'(x^*)-\theta'(x^*)f(x^*)>0,$$

where the first inequality follows from the first part of (7), that is, $f'(x^*)-w>0$. The second inequality follows from the fact that $f(x^*)>wx^*$. This is because if $f(x^*)<wx^*$, then the expected utility equation (1) evaluated at x^* will be less than $U(Y)$, implying that the farmer would be better off by choosing $x=0$. This contradicts with the

fact that x^* is defined as the optimal solution to maximization problem (1). Finally, the last inequality follows from the second part of (7).

Since both parts of (6) are positive, we can conclude that the first order condition (5) evaluated at x^* is positive, which means further increasing input beyond x^* will increase the expected utility defined in (2). This implies $x_I^* > x^*$ and completes the proof.

Remark: Intuitively, insurance coverage has two effects on the farmer's incentives to use inputs. First, insurance reimburses part of the input costs when there is a disaster. As a result, the effective unit cost for inputs is reduced from w to $\theta(x)w$ when there is a disaster. This effect is captured by the second part of (6). Second, having insurance increases the wealth of the farmer when a disaster hits but does not change the wealth of the farmer where there is no disaster. This reduces the range of possible outcomes and hence makes the input investment decision less risky for the farmer. This effect is captured by the first part of (6). Both effects give the farmer incentives to use more inputs.

As mentioned above, in the Philippines corn crop insurance program, in addition to have the input cost covered, farmers also have the option to choose to have up to 20% of their expected yields covered. The following corollary shows that when farmers exercise this option, our theorem above continues to hold.

Corollary: Under the assumptions made above and the farmer also chooses to have up to 20% of his expected yield covered under the crop insurance program, then $x_I^* > x^*$.

Proof: Suppose the representative farmer participates in the insurance program and chooses to have r of his expected yield ($0 < r < 0.2$) covered by the insurance. The theorem above shows that when only input costs are covered, the farmer would use more

inputs. Therefore, if we can also show that the farmer would use more inputs when only r of his expected yield is covered, then we can conclude that the farmer would use more inputs when both his input costs and r of his expected yield are covered.

The farmer's expected utility when only r of his expected yield is covered is the following,

(9) $$EU = (1-\rho)U[f(x) - wx + Y] + \rho U[f(x) - wx + Y], \quad \text{if } 1-\theta(x) \leq r$$

$$EU = (1-\rho)U[f(x) - wx + Y] + \rho U[(\theta(x) + r)f(x) - wx + Y], \text{ if otherwise.}$$

Denote x_{max} as the solution to $f'(x) = w$. x_{max} is the optimal amount of input choice when the farmer faces no risk of loss in yield. Since any risk of loss in yield reduces the marginal return from input investment, we know that as long as the risk of loss is not zero, the farmer will use less input so x_{max} is the maximum amount of input that will be used by the farmer.

If $1-\theta(x_{max}) \leq r$, then $x_I^* = x_{max}$. This is because when $1-\theta \leq r$ and there is a loss, the indemnity payments will equal to the amount of loss in yield and hence effectively the farmer faces no risk. Since $f'(x^*) > w$ (see (7)) and $f'' < 0$, we can conclude that $x_I^* > x^*$.

On the other hand, if $1-\theta(x_{max}) > r$, then we have $1-\theta(x) > r$ for any $x < x_{max}$ because $\theta'(x) > 0$. In this case, the farmer's expected utility function is represented by the second line of (9). Then, by definition, x_I^* is the solution to the following first order condition,

(10) $$(1-\rho)\frac{f'(x_I^*) - w}{(f(x_I^*) - wx_I^* + Y)^2} + \rho\frac{[\theta(x_I^*) + r]f'(x_I^*) + \theta'(x_I^*)f(x_I^*) - w}{[(\theta(x_I^*) + r)f(x_I^*) - wx_I^* + Y]^2} = 0.$$

Similar to the proof for the case where only the input costs are covered, plugging the optimal amount of input use under no insurance x^* into (10) and using (4) yield,

(11) $$(1-\rho)\frac{f'(x^*)-w}{[f(x^*)-wx^*+Y]^2}+\rho\frac{\theta'(x^*)f\quad(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}-$$

$$\rho\frac{\theta'(x^*)f\quad(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}+\rho\frac{[\theta(x^*)+r]f'(x^*)+\theta'(x^*)f(x^*)-w}{[(\theta(x^*)+r)f(x^*)-wx^*+Y]^2}=$$

$$\rho\left\{\frac{\theta(x^*)f'(x^*)+\theta'(x^*)f(x^*)-w}{[(\theta(x^*)+r)f(x^*)-wx^*+Y]^2}-\frac{\theta'(x^*)f\quad(x^*)+\theta(x^*)f'(x^*)-w}{[\theta(x^*)f(x^*)-wx^*+Y]^2}\right\}+$$

$$\rho\frac{rf'(x^*)}{[(\theta(x^*)+r)f(x^*)-wx^*+Y]^2}.$$

The first part of (11) (the term inside the bracket) is positive because the two terms inside the bracket share the same negative numerator and the denominator of the first term is larger than that of the second term. The second part of (11) is also positive because $f'>0$. Since both parts of (11) are positive, we can conclude that the first order condition (10) evaluated at x^* is positive, which means further increasing input beyond x^* will increase the expected utility defined in the second line of (9). This implies $x_I^*>x^*$ and completes the proof.

Another case is when the assumption (3) does not hold, which is the case for some damage control inputs, such as pesticides. For this case, the first part in (6) turns to be negative while the sign of the second part is ambiguous. Thus, it is still possible to have $x_I^*>x^*$.

To sum up, based on this model, for yield-enhancing inputs, the input use under insurance is larger than without insurance, and for damage-control inputs, the effect of insurance on input use is uncertain.

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 for the survey using the multi-stage stratified random sampling approach. Two municipalities from each province were chosen based on the area devoted to corn production and the number of producers enrolled in PCIC corn insurance program. The data on the area devoted to corn and the number of insured producers 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. In each stratum, 213 farmers were chosen randomly. The list of insured corn farmers was provided by PCIC and the list of non-insured farmers were obtained from village heads. 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 indicators of cognitive ability and cautiousness).

A few farmers were dropped from the sample. First, those farmers who used open-pollinated seeds were dropped because the yields for open-pollinated seeds are usually lower and hence farmers who use this type of seeds may behave quite differently from farmers who purchase seeds. Second, farmers who were paid care-takers of the fields were dropped because they usually do not make insurance purchase and input use decisions. Finally, some farmers reported unrealistically high per hectare yields and these numbers were likely due to measurement errors. Thus, considering the average mean yield is just five thousand kilogram per hectare, those farmers with historical mean yields larger than 12,000 kg per hectare were dropped from this sample. As a result, there are 380 farmers in our working sample.

Empirical Strategy

We test our hypothesis, that is, insurance has a positive effect on input use, by estimating the following empirical model,

(12) $$y_i = \beta_0 + \beta_1 Insurance_i + \beta_2 X_i + u_i,$$

where y_i is the amount of input used. We consider the amounts of fertilizer ($Fertilizer_i$), weedicides ($Weedicide_i$) and pesticide ($Pesticide_i$) used per hectare as well as the total expenditure on these three inputs ($Expenditure_i$). $Insurance_i$ is the dummy variable indicating whether insurance is purchased or not. The vector X_i includes farmer i's characteristics that can potentially influence the amount of input used. Below we discuss the definition of each variable and the reasons to include them in the regressions.

Since each farmer has land with different quality, faces different weather conditions, and uses different technology, we include the average yield per hectare of the two most recent years, that is, 2010 and 2011, ($HistoricalYield_i$) in the regressions to control for the effect of unobserved individual heterogeneity that are not captured by the province dummies on input use.[24]

Input decisions also depend on the type of seeds used. The $Hybrid_i$ variable is equal to 1 if farmer i uses hybrid seeds and 0 if GMO or BT seeds are used. Newly developed GMO and BT seeds offer various new features, such as inherent resistance to pests such Asian corn borers so less pesticides will be used and herbicide tolerance so that farmers can apply more weedicides without damaging the plant.

The variable $DistanceRoad_i$ is the distance between farmer i's fields and the nearest road. Because transportation cost is part of the input cost, the distance to the nearest road can affect farmers' input use decisions. Moreover, in remote areas, jfarmers have little outside job opportunities and other sources of income. As a result, they may tend to use more inputs to ensure good yields.

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 examine the wealth effect on input use. Also, the area variable reflects the scale of the farm and captures any returns to scale effect on input use.

Two variables are used to account for farms' diversification. $Livestock_i$ is set to be 1 if the farmer raises any livestock and 0 otherwise. Farmers can apply livestock

[24] For those respondents who could not recall the yields of these two years, the values for this variable are denoted as missing.

manure to their fields instead of fertilizers. $OtherCrop_i$ is set to be 1 if the farmer plants other crops aside from corn and 0 otherwise. Farmers who grow other crops face less risks due to diversification. For example, the damage from corn-borne pests and diseases are more likely to be restricted to the corn planted parcel and as a result, farmers may use less pesticides.

A risk aversion measure ($RiskAverse_i$) is also included in the regression because risk-averse farmers may use the most conservative approach such as using more chemicals to minimize uncertainty in their farming income. Farmers' risk preference is elicited by a hypothetical question asking whether they are willing to try a new seed variety that may double their yield or cut their yield by several given proportions (20%, 50% and 75%). Those farmers who are not willing to try this risky seed even when it has only half chance of decreasing their yields by 20% are considered to be the most risk-averse ones, and $RiskAverse_i$ is set to be 1 for these farmers. The variable takes the value of 0 for other farmers. Finally, province dummies are included to control for heterogeneity in input prices or any other effects that vary at the regional level.

Identification

One challenge in estimating (12) is that the insurance variable, $Insurance_i$, might be endogenous. For example, a farmer may possess some private information that his fields have a high probability of being struck by pests in the coming year. As a result, he purchases insurance and also uses more pesticides to minimize the expected loss. To correct for this potential endogeneity bias, we use the instrumental variable approach. For

a variable to be a good instrument, it has to satisfy two conditions. First, it has to be excluded from (12), that is, it should have no effect on input use once X_i is controlled for. Put in other words, it needs to be uncorrelated with the error term u_i in (12). Second, it has to be correlated with the potentially endogenous variable, that is, the insurance variable. Although the second condition can be tested directly by examining the first stage estimation results from the two-stage least squares IV estimation, the first condition can only be tested indirectly through the overidentification test. Below, we identify three variables in our dataset that can potentially be used as instrumental variables and then discuss under what assumptions they are valid instruments. We also perform statistical tests to examine the validity of these instruments.

Our first instrumental variable is $Credit_i$, which is the total amount of loan farmer i borrows. One section in the survey is on sources of capital. It asks farmers to report the sources and the amount of their borrowings. The sources can be official or private lending institutions, banks, relative and others. In the Philippines, those who borrow from official lending institutions are required to purchase insurance and some farmers who borrow from other channels are also required to purchase insurance. Therefore, the amount of loan certainly has an impact on the likelihood of purchasing insurance. On the other hand, if a farmer cannot borrow all the money he needs to purchase inputs, then the more he can borrow, the more inputs he will use. In the Philippines, this is unlikely to be the case, at least for those farmers who borrow from official lending institutions. For these farmers, they submit a Farm and Budget Plan stating the amounts of inputs they plan to use and the amount of loan they need to

purchase these inputs as part of their loan application. As the government has been very supportive of farming, it usually approves the requested amount of loan. Therefore, under the assumption that farmers have no problem borrowing the money needed to purchase inputs, this variable is a valid instrument.

Our second instrumental variable is organization membership (Org_i), which is equal to 1 if farmer i is a member of any organization, which includes farmers organizations, civic organizations, and religious organizations and 0 otherwise. In the Philippines, farmers can purchase crop insurance as a group. This may significantly reduce the burden of document preparation and increase the likelihood for crop insurance participation. On the other hand, the effect from organization membership on farming practices is far from being direct. Farmers make their input use decisions mainly based on the quality of their land and their experiences in farming and by listening to agricultural technicians and following the instruction manuals for the chemicals. Therefore, under the assumption that organization membership has little effect on input use, this is a valid instrument.

Our third and final instrument is a measure of farmers' perception on the usefulness of crop insurance. One question in the survey asks whether they agree that buying crop insurance can manage the risks of crop failure. If farmer i believes crop insurance is a useful tool to manage risks, the variable $Useful_i$ is set to be 1. It is set to be 0 otherwise. Obviously, farmers who believe crop insurance is a useful tool to manage farming risk are more likely to purchase insurance. On the other hand, farmers perception

of the usefulness of crop insurance should have little effect on their farming practices and their input uses in particular.

All the variables discussed in this section, together with their definitions, are listed in Table 2.1. The summary statistics for these variables are reported in Table 2.2.

Estimation Results

We estimate (12) using two-stage least squares (2SLS). The first-stage estimation results are reported in Table 2.3. All of the three instrumental variables have a positive (as expected) and statistically significant effect on insurance purchase. The F statistic for the joint hypothesis that none of the three instrumental variables has any effect on insurance purchase is larger than 10, indicating that we can reject the hypothesis that the IV regression is weakly identified. This verifies that our instruments are correlated with the potential endogenous variable.

The second-stage estimation results are reported in Table 2.4. Several results are worth discussing. First, the overidentification test results indicate that we cannot reject the hypothesis that our instruments are valid. Second, crop insurance is found to have a positive effect on the use of fertilizer, weedicide and pesticide as well as the total expenditure on chemicals. Three out of the four estimated effects are statistically significant. The magnitudes of the effects are not small. For example, insured farmers use 53 more kilograms of fertilizers per hectare than uninsured farmers. This is equivalent to about 12% of the average amount of fertilizers used by farmers in the dataset. These results lend empirical support to our Theorem above and show that when insured farmers

are being monitored, there is no room for moral hazard behavior and they are willing to spend more on inputs. Note that the reason that the effect of insurance is not significant on pesticides is explained in the model section. It is because the positive effect of insurance on input use is predicted for more yield-enhancing rather than damage-control inputs.

Third, farmers with higher yields in the past use more fertilizer and spend more on chemicals. They are also found to use more weedicides and pesticides, but the effects are not statistically significant. As discussed above, historical yields capture unobserved individual heterogeneity. One reason that some farmers had high yields in the past could be that these farmers tend to apply more chemicals to their lands than others. Fourth, farmers that are located farther away from roads are found to use more fertilizers and chemicals as a whole. Also, they are found to use more weedicides and pesticides, though the effects are not statistically significant. In remote areas, farmers have little outside job opportunities and other sources of income. As a result, they may tend to use more inputs to ensure good yields.

Fifth, diversified farmers are found to use less fertilizers and chemicals as a whole. They are also found to use less weedicides and pesticides, though the effects are not statistically significant. Farmers who also grow livestock can use animal manure as an alternative to commercial fertilizer and hence use less fertilizers. Also, for these farmers, their sources of income are diversified so they have less incentives to use inputs to boost their yields. Sixth, risk-averse farmers use more fertilizers and spend more on all inputs combined. They are also found to use more weedicides and pesticides, though the effects

are not statistically significant. This is consistent with the idea that risk averse farmers are willing to invest more in inputs to minimize the chances of crop failure.

Finally, we also tested whether the insurance variable is endogenous or not using the Hausman test and results there indicate that we cannot reject the hypothesis that the insurance variable is actually exogenous. This is actually not surprising because in the Philippines crop insurance market, many farmers do not purchase insurance voluntarily. Those farmers who borrow from official lending institutions are required to purchase insurance and some farmers who borrow from other channels are also required to purchase insurance. Therefore, (12) is also estimated using OLS and the results are collected in Table 2.5. The OLS results are very similar to the 2SLS results, both in terms of statistical significance and magnitudes of the effects with the only exception that insurance is found to have a smaller effect on fertilizers and weedicides. But the absolute value of the estimates are still not trivial and statistically significant. For example, the 2SLS results show that on average insured farmers use 53 more kilograms of fertilizers per hectare than uninsured farmers, while the OLS results show insured farmers use 30 more kilograms of fertilizers per hectare than uninsured farmers.

Robustness checks

Although the overidentification test and the first-stage F test results above suggest that we cannot reject the hypothesis that the three instrumental variables used are valid, we also cannot rule out the possibility that any or all of them are invalid. The variable $Credit_i$ causes some concern. For example, farmers who have loans can be under higher pressure

to produce more corn. However, from the discussion of those variables above, it is clear that the variable $Useful_i$ appears to require the weakest assumptions to be used as a valid instrumental variable. Therefore, in our first robustness check, we drop $Credit_i$ and use both the $Organization_i$ and the $Useful_i$ variables as the instrumental variables in our instrumental variable regression. Estimation results are reported in Tables 2.6 and 2.7. The first-stage results in Table 2.6 show that $Credit_i$ and $Useful_i$ still has positive and statistically significant effects on insurance purchase. The F statistic for the joint hypothesis that neither of the two instrumental variables has any effect on insurance purchase is very close to 10 (at 9.7), implying that the IV regression is not weakly identified. The second-stage estimation results are consistent with our main results above. The insurance effects on fertilizer, weedicide and total chemical use are positive and statistically significant The estimated magnitudes are slightly larger compared to the 2SLS results when all three instrumental variables are used.

In our second robustness check, we use only the $Useful_i$ variables as the instrumental variable in our instrumental variable regression. Estimation results are reported in Tables 2.8 and 9. The first-stage results in Table 2.8 show that $Useful_i$ has a positive and statistically significant effect on insurance purchase, rejecting the hypothesis that this IV regression is weakly identified. The second-stage estimation results are consistent with our main results above. The insurance effect on fertilizer use is positive and statistically significant at 5% and its effect on total expenditure for chemical inputs is positive and statistically significant at 11%. The estimated magnitudes are similar to previous robustness check.

Another concern is that the short-run decision of seed choice could be endogenous as well. To address this concern, we drop the $Hybrid_i$ variable and run the main regression again (see Table 2.10 and Table 2.11). The results are almost identical to the specification with the variable of $Hybrid_i$.

Our last robustness check uses the propensity score matching (PSM) method to estimate the effect of insurance on input use (e.g. Rosenbaum and Rubin, 1983). The PSM approach relies on a different set of assumptions than the IV regression approach to identify the causal effect. Specifically, the unconfoundedness assumption has to be satisfied, which assumes that the potential treated or untreated outcomes are independent of the treatment status conditional on a set of variables, which are called confounders. In our context, treatment refers to having insurance and the confounders are the X variables in (12). To implement this approach, we first estimate a logit model to calculate the probability (the propensity score) for each farmer to have insurance. Then, for each farmer with insurance, we match him with one, five or ten uninsured farmers who have the smallest differences between their propensity scores and his score. For each uninsured farmer, we match him with one, five or ten insured farmers who have the smallest differences between their propensity scores and his score. Next, we compute the difference between a farmer's input use with the average of his matched farmers. Finally, we average the differences across all farmers to obtain the average treatment effect.

The PSM estimation results in Table 2.12 show once again that having insurance significantly increases fertilizer use, weedicides use (for one to five and one to ten matching results) and total expenditure on chemicals. In addition, the magnitudes of the

effects for fertilizers and weedicides are very close to those of OLS but smaller than those of 2SLS. The insurance effect on total chemical expenditure is very similar to both OLS and 2SLS results. Therefore, we conclude that the PSM results are consistent with our main results above.

Conclusion

In this paper, we test whether monitoring is an effective method to curb moral hazard behavior by the farmers in crop insurance programs. Our theoretical model predicts that if monitoring is effective, insured farmers will use more of yield-enhancing inputs than their uninsured counterparts. Using data from corn farmers in the Philippines, we found indeed insured farmers used more of certain chemicals during the growing season than uninsured farmers. Our results are robust to several specification checks. Therefore, we conclude that monitoring is an effective way to curb moral hazard behavior.

Our analysis provides valuable information for other countries, especially those whose crop insurance programs are failing or becoming too expensive because of moral hazard. Our results suggest that the moral hazard problem can be alleviated if there are mechanisms in place to monitor farmers' behavior during production.

Several related questions remain unanswered. First, though monitoring can reduce the cost associated with moral hazard, it is costly in itself. Therefore, the natural question to ask next is whether monitoring can pay for itself. Second, as mentioned above, there are other ways to curb the moral hazard problem such as setting premiums based on past claim histories or decreasing the indemnity payments as a percentage of the losses. It

would be interesting to compare all these alternative strategies to curb moral hazard in terms of effectiveness and costs. These are left for future research.

REFERENCES

Babcock, B. A., and D. A. Hennessy. 1996. “Input demand under yield and revenue insurance.” *American journal of agricultural economics* 78(2): 416-427.

Bellemare, M. F. 2010. “Agricultural extension and imperfect supervision in contract farming: evidence from Madagascar.” *Agricultural Economics* 41(6): 507-517.

Chiappori, P. A., F. Durand, and P. Y. Geoffard. 1998. “Moral Hazard and the Demand for Physician Services: First Lessons From a French Natural Experiment.” *European Economic Review* 42: 499-511.

Dionne, G., M. Maurice, J. Pinquet, and C. Vanasse. 2005. “The Role of Memory in Long-Term Contracting With Moral Hazard: Empirical Evidence in Automobile Insurance.” Social Science Research Network. No. 764705.

Frisvold, G. B.1994. "Does supervision matter? Some hypothesis tests using Indian farm-level data." *Journal of Development Economics* 43(2): 217-238.

Goodwin, B.K., M.L. Vandeveer, and J. Deal. 2004. “An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program.” *American Journal of Agricultural Economics* 86(4): 1058-1077.

Horowitz, J. K., and E. Lichtenberg. 1993. “Insurance, moral hazard, and chemical use in agriculture. “ *American Journal of Agricultural Economics* 75(4): 926-935.

International Fund for Agricultural Development. 2011. *Rural Poverty Report. New Realities, New Challenges: New Opportunities for Tomorrow’s Generation*. Rome, Italy.

Jacoby, H. G., and G. Mansuri. 2009. “Incentives, supervision, and sharecropper productivity.” *Journal of Development Economics* 88(2): 232-241.

Quiggin, J., G. Karagiannis, and J. Stanton. 1993. "Crop Insurance and Crop Production: An Empirical Analysis Study of Moral Hazard and Adverse Selection." *Australian Journal of Agricultural Economics* 37 (2): 95-113.

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.

Rosenbaum, P. R., and Rubin, D. B. 1983. “The central role of the propensity score in observational studies for causal effects.” *Biometrika* 70(1): 41-55.

Smith, V. H., and B. K. Goodwin. 1996. “Crop insurance, moral hazard, and agricultural chemical use.” *American Journal of Agricultural Economics*. 78(2): 428-438.

Weber, J. G., N. Key, and E. J. O’Donoghue. 2015. “Does Federal Crop Insurance Encourage Farm Specialization and Fertilizer and Chemical Use?” Paper presented at AAEA and WAEA Annual Meetings, San Francisco, CA, 26-28 July.

Wu, J. 1999. Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution. American *Journal of Agricultural Economics* 8:305-320.

Yorobe, Jr. J. M., and P. M. Luis. 2015. *Improving the Agricultural Insurance Program to Enhance Resilience to Climate Change: Evidence from Corn Production in the Philippines*. Laguna, Philippines: Southeast Asian Regional Center for Graduate Study and Research in Agriculture, Technical report, January.

Table 2.1 List of Variables

Variable	**Unit**	**Definition**
Dependent variables		
Fertilizer	100 kilograms/hectare	Total kilograms of fertilizer applied per hectare
Pesticide	Kilogram /hectare	Total kilograms of pesticides applied per hectare
Weedicide	Kilogram /hectare	Total kilograms of weedicides applied per hectare
Expenditure	10,000 PHP	Total expenditure on chemical inputs
Independent variables		
Insurance		1=having insurance and 0 otherwise
HistoricalYield	1,000 kg/hectare	Mean yield per hectare of 2010 and 2011
Hybrid		1=hybrid varieties and 0 otherwise
DistanceRoad	Kilometer	Distance to nearest market
Area	Hectare	Total area of planted fields
Livestock		1=farmer raise any livestock and 0 otherwise
OtherCrop		1=farmer plants other crops aside from corn and 0 otherwise
RiskAverse		1= most risk-averse farmer and 0 otherwis
Isabella		1=Isabela and 0 otherwise
Pangasinan		1=Pangasinan and 0 otherwise
Instrumental variables		
Credit	10,000 PHP	Total amount of loan
Org		1=with membership in any organization and 0 otherwise
Useful		1=farmer believes insurance can manage the risks of crop failure and 0 otherwise

Table 2.2 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Fertilizer	380	4.4187	1.4394	0.54	9.67
Pesticides	380	0.4346	1.8184	0	30
Weedicides	380	4.4714	3.3356	0	24
Expenditure	380	1.1853	0.3636	0.19	2.57
Insurance	380	0.5132	0.5005	0	1
HistoricalYield	380	4.9322	2.2122	0	12
Hybrid	380	0.7053	0.4565	0	1
DistanceRoad	372	0.9731	1.8117	0	20
Area	373	2.4925	2.3741	0.25	26
Livestock	380	0.1553	0.3626	0	1
OtherCrop	380	0.5263	0.5000	0	1
RiskAverse	380	0.1921	0.3945	0	1
Isabella	380	0.3526	0.4784	0	1
Pangasinan	380	0.3158	0.4654	0	1
Credit	379	3.1523	3.7138	0	34.50
Org	380	0.5026	0.5007	0	1
Useful	378	0.7989	0.4013	0	1

Table 2.3 First-Stage Estimation

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0275	0.01*
Hybrid	0.0135	0.05
DistanceRoad	0.0039	0.01
Area	-0.0178	0.01*
Livestock	0.0572	0.06
OtherCrop	-0.0807	0.06
RiskAverse	-0.0312	0.06
Isabella	-0.0067	0.06
Pangasinan	0.0333	0.07
Credit	0.0389	0.01***
Org	0.2793	0.05***
Useful	0.3528	0.06***
_cons	-0.1184	0.10
N of obs.	363	
F Stat. for Instruments	12.72	
Adj. R^2	0.28	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.4 Second-Stage Estimation

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.5281**	0.25	1.0804**	0.57	0.3712	0.37	0.1175*	0.07
HistoricalYield	0.0622*	0.03	0.1222	0.08	0.0458	0.05	0.0263***	0.01
Hybrid	0.1075	0.15	0.4814	0.35	0.0038	0.22	-0.0208	0.04
DistanceRoad	0.0810*	0.04	0.0778	0.08	0.0040	0.05	0.0246***	0.01
Area	0.0228	0.03	-0.0517	0.07	0.0407	0.05	0.0003	0.01
Livestock	-0.0493	0.18	-0.4716	0.42	-0.2437	0.27	-0.0261	0.05
OtherCrop	-0.3722***	0.16	-0.4642	0.36	-0.1876	0.23	-0.0902**	0.04
RiskAverse	0.6492***	0.17	0.1834	0.38	0.6254	0.25	0.1561***	0.04
Isabella	-0.5768***	0.17	-0.0208	0.39	0.4729**	0.25	-0.1092***	0.05
Pangasinan	1.0437***	0.19	-3.6531***	0.43	0.0179	0.28	0.1482***	0.05
_cons	3.5802***	0.25	4.4453***	0.57	-0.2368	0.37	0.9939***	0.07
N of obs.	363		363		363		363	
R^2	0.2976		0.0395		0.0395		0.1904	
Overidentification test		P-Value		P-Value		P-Value		P-Value
Sargan $\chi^2(2)$	1.1653	0.5584	1.9360	0.3798	0.9421	0.6243	0.3659	0.8328
Basmann $\chi^2(2)$	1.1272	0.5692	1.8767	0.3913	0.9108	0.6342	0.3532	0.8381
Endogeneity Test		P-Value		P-Value		P-Value		P-Value
Wu-Hausman F test statistic	1.4383	0.2312	1.0221	0.3127	0.0688	0.7932	0.1189	0.7304

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.5 Ordinary Least Square Estimation

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.2985**	0.13	0.5804**	0.30	0.2838	0.20	0.1030***	0.04
HistoricalYield	0.0654*	0.03	0.1399*	0.08	0.0490	0.05	0.0258***	0.01
Hybrid	0.0780	0.15	0.4960	0.35	0.0062	0.23	-0.0275	0.04
DistanceRoad	0.0844***	0.04	0.0892	0.08	0.0063	0.05	0.0245***	0.01
Area	0.0243	0.03	-0.0472	0.07	0.0408	0.05	0.0005	0.01
Livestock	-0.0354	0.18	-0.4183	0.42	-0.2327	0.27	-0.0270	0.05
OtherCrop	-0.3727***	0.16	-0.4878	0.37	-0.1920	0.24	-0.0888**	0.04
RiskAverse	0.6111***	0.17	0.1480	0.39	0.6226***	0.25	0.1500***	0.05
Isabella	-0.5862***	0.17	-0.0236	0.39	0.4717*	0.25	-0.1107***	0.05
Pangasinan	1.0811***	0.19	-3.6648***	0.43	0.0102	0.28	0.1575***	0.05
_cons	3.7003***	0.24	4.5901***	0.55	-0.2107	0.36	1.0084***	0.07
N of obs.	365		365		365		365	
Adj. R^2	0.2870		0.2542		0.0130		0.1703	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.6 First-Stage Estimation (using *Organization* and *Useful* as the instrument)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0322***	0.01
Hybrid	0.0602	0.06
DistanceRoad	0.0128	0.01
Area	-0.0022	0.01
Livestock	0.0821	0.07
OtherCrop	-0.1274**	0.06
RiskAverse	-0.0538	0.06
Isabella	0.0637	0.06
Pangasinan	0.1102	0.07
Org	0.2890***	0.05
Useful	0.4042***	0.06
_cons	-0.1705*	0.10
N of obs.	364	
F Stat. for Instruments	9.72	
Adj. R^2	0.21	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.7 Second-Stage Estimation (using *Organization* and *Useful* as the instrument)

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.6960***	0.29	1.4883**	0.67	0.1600	0.43	0.1435**	0.08
HistoricalYield	0.0566*	0.03	0.1084	0.08	0.0529	0.05	0.0254***	0.01
Hybrid	0.1061	0.15	0.4747	0.35	0.0062	0.22	-0.0207	0.04
DistanceRoad	0.0770**	0.04	0.0687	0.08	0.0090	0.05	0.0239***	0.01
Area	0.0221	0.03	-0.0550	0.07	0.0418	0.04	0.0004	0.01
Livestock	-0.0683	0.18	-0.5141	0.43	-0.2204	0.27	-0.0294	0.05
OtherCrop	-0.3648**	0.16	-0.4462	0.37	-0.1969	0.23	-0.0891**	0.04
RiskAverse	0.6587***	0.17	0.2141	0.39	0.6121***	0.25	0.1568***	0.04
Isabella	-0.5742***	0.17	-0.0171	0.39	0.4701*	0.25	-0.1085***	0.05
Pangasinan	1.0507***	0.19	-3.6476***	0.43	0.0109	0.28	0.1505***	0.05
_cons	3.5257***	0.25	4.3190***	0.59	-0.1692	0.38	0.9848***	0.07
N of obs.	364		364		364		364	
R^2	0.2866		0.2543		0.0389		0.1887	
Overidentification test		P-Value		P-Value		P-Value		P-Value
Sargan $\chi^2(2)$	0.0016	0.9676	0.554	0.4567	0.1065	0.7441	0.0303	0.8619
Basmann $\chi^2(2)$	0.0016	0.9682	0.5365	0.4639	0.103	0.7482	0.0293	0.8642
Endogeneity Test		P-Value		P-Value		P-Value		P-Value
Wu-Hausman F test statistic	2.6264	0.106	2.2636	0.1333	0.1023	0.7492	0.4052	0.5248

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.8 First-Stage Estimation (using only *Useful* as the instrument)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0279**	0.01
Hybrid	0.0368	0.06
DistanceRoad	0.0246*	0.01
Area	0.0038	0.01
Livestock	0.1216*	0.07
OtherCrop	-0.0573	0.06
RiskAverse	-0.0815	0.06
Isabella	0.0795	0.07
Pangasinan	0.1331*	0.07
Useful	0.4626***	0.06
_cons	-0.1079	0.11
N of obs.	364	
Adj. R^2	0.14	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.9 Second-Stage Estimation (using only *Useful* as the instrument)

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.7048**	0.36	1.1123	0.83	0.0544	0.54	0.1537	0.10
HistoricalYield	0.0563*	0.03	0.1211	0.08	0.0565	0.05	0.0251***	0.01
Hybrid	0.1059	0.15	0.4810	0.35	0.0079	0.22	-0.0209	0.04
DistanceRoad	0.0768**	0.04	0.0771	0.08	0.0114	0.05	0.0237***	0.01
Area	0.0221	0.03	-0.0519	0.07	0.0427*	0.05	0.0003	0.01
Livestock	-0.0692	0.18	-0.4751	0.43	-0.2094	0.28	-0.0304	0.05
OtherCrop	-0.3644**	0.16	-0.4627	0.36	-0.2015	0.24	-0.0886**	0.04
RiskAverse	0.6594***	0.17	0.1855	0.39	0.6041***	0.25	0.1576***	0.05
Isabella	-0.5741***	0.17	-0.0204	0.39	0.4692	0.25	-0.1085***	0.05
Pangasinan	1.0508***	0.19	-3.6522***	0.43	0.0096	0.28	0.1506***	0.05
_cons	3.5230***	0.26	4.4351***	0.60	-0.1366	0.39	0.9817***	0.07
N of obs.	364		364		364		364	
R^2	0.2857		0.2663		0.0362		0.1869	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.10 First-Stage Estimation (Dropping the *Hybrid* variable)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0276***	0.01
DistanceRoad	0.0040	0.01
Area	-0.0177*	0.01
Livestock	0.0555	0.06
OtherCrop	-0.0813	0.06
RiskAverse	-0.0304	0.06
Isabella	-0.0113	0.06
Pangasinan	0.0327	0.07
Credit	0.0391***	0.01
Org	0.2783***	0.05
Useful	0.3519***	0.06
_cons	-0.1068	0.09
N of obs.	363	
F Stat. for Instruments	13.91	
Adj. R^2	0.2817	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.11 Second-Stage Estimation ((Dropping the *Hybrid* variable))

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.5279**	0.25	1.0808*	0.57	0.3724	0.37	0.1172*	0.07
HistoricalYield	0.0629*	0.03	0.1254	0.08	0.0458	0.05	0.0261***	0.01
DistanceRoad	0.0817**	0.04	0.0807	0.08	0.0040	0.05	0.0245***	0.01
Area	0.0244	0.03	-0.0446	0.07	0.0407	0.04	0.0000	0.01
Livestock	-0.0630	0.18	-0.5330	0.42	-0.2443	0.27	-0.0234	0.05
OtherCrop	-0.3821***	0.16	-0.5085	0.36	-0.1879	0.23	-0.0883**	0.04
RiskAverse	0.6553***	0.17	0.2111	0.39	0.6257***	0.25	0.1549***	0.04
Isabella	-0.6100***	0.16	-0.1697	0.37	0.4718**	0.24	-0.1028***	0.04
Pangasinan	1.0445***	0.19	-3.6498***	0.43	0.0179	0.28	0.1481***	0.05
_cons	3.6659***	0.22	4.8282***	0.50	-0.2341	0.33	0.9774***	0.06
N of obs.	363		363		363		363	
R^2	0.2966		0.3035		0.0395		0.1899	
Overidentification test		P-Value		P-Value		P-Value		P-Value
Sargan	0.8938	0.6396	1.3407	0.5115	0.9268	0.6291	0.4572	0.7957
Basmann	0.8664	0.6484	1.3012	0.5217	0.8985	0.6381	0.4426	0.8015
Endogeneity Test		P-Value		P-Value		P-Value		P-Value
Wu-Hausman F test statistic	1.4227	0.2338	0.9981	0.3185	0.0709	0.7902	0.1188	0.7305

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 2.12 Propensity Score Matching Estimation

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
ATE （1 to 1)								
Insurance	0.2825**	0.14	0.5641	0.36	0.1605	0.14	0.1010***	0.04
ATE (1 to 5)								
Insurance	0.3162***	0.13	0.5517*	0.31	0.2037	0.16	0.1057***	0.04
ATE (1 to 10)								
Insurance	0.3097**	0.14	0.6805**	0.32	0.2269	0.18	0.1006***	0.04
N of obs.	365		365		365		365	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Chapter 3 Estimating Adverse Selection and Moral Hazard Effects in Crop Insurance: Evidence from the Philippines

Introduction

Crop insurance plays an important role in the agricultural sector. Not only does it stabilize farmers' income, but it also reduces the cost of risk-bearing and encourages farmers to assume more risks such as making investments in new technology. Crop insurance is even more important for developing countries, where the agricultural sector still accounts for a large share of the GDP and provides critical inputs for other sectors. Crop failures have more serious and disruptive impact on the national economy in these countries than in more developed one. This is the reason why developing, promoting and maintaining a healthy crop insurance program has been a top agricultural agenda in many developing countries since the last century.

However, there is a great deal of concern on the efficiency and sustainability of crop insurance programs around the world. Among other things, moral hazard and adverse selection are identified as the two main problems. Moral hazard happens when insured farmers worry less about loss, take less care of their fields (i.e. use less input) and

as a result, are more likely to experience a loss. See Smith and Goodwin (1996), Knight and Coble (1997), and Roberts, Key, and O'Donoghue (2006) for studies of moral hazard in crop insurance. Adverse selection arises because high-risk agents are more likely to purchase insurance as they perceive larger benefit from participating. As a result, indemnity payments are higher than premium collected. See Goodwin (1993), Quiggin, Karagianis, and Stanton (1993), Smith and Baquet (1996), Just, Calvin and Quiggin (1999), Makki and Somwaru (2001), Garrido and Zilberman (2008) and Hou, Hoag, and Mu (2011) for studies of adverse selection in crop insurance. Different strategies are needed to deal with the two problems. For moral hazard, setting premiums based on historical records, partial coverage, as well as monitoring can lower farmers' incentives to engage in moral hazard behavior. For adverse selection, better rate-setting schemes need to be developed and employed to make premiums correctly reflect individuals' risk levels.

Therefore, to identify the need and the correct strategies to improve the crop insurance programs, we need to know whether the programs under consideration suffer from moral hazard or adverse selection or both and the magnitudes of these effects. However, it is well known that separately identify and estimate the two effects is a challenging task because the empirical evidence for both effects is the same, that is, we observe insured farmers under crop insurance are more likely to experience a loss. Only under rare scenarios, the two can be disentangled from each other. For example, Gunnsteinsson (2014) designed a field experiment in which farmers were first asked to select a plot which they preferred to get insured and then insurance was randomly

assigned to plots. In this way, farmers' plot-level moral hazard can be separately identified and estimated from adverse selection by comparing outcomes from preferred but not insured, preferred and insured, and not preferred but insured plots. In another study, Liu, Nestic and Vukina (2012) use data in the Croatian health insurance market to estimate adverse selection effect by comparing health expenditures by those who bought supplemental insurance and those who are given supplemental insurance for free, and estimate moral hazard effect by comparing individuals who got free supplemental insurance and who had no insurance.

In this paper, using a survey question that elicits farmers' true preference for corn insurance, we separately identify and estimate the moral hazard and adverse selection effects of crop insurance in the Phillipines. To the best of our knowledge, our paper is the first effort to disentangle moral hazard and adverse selection effects in the context of crop insurance. In the Philippines, farmers are required to purchase insurance if they borrow from official lending institutions, and 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 with a true demand for crop insurance. Therefore, the difference in outcomes between the farmers with a true demand for insurance and those who were forced to purchase is caused by adverse selection, while the difference in outcomes between the farmers who were forced to purchase and those who did not purchase is caused by moral hazard.

Propensity score matching is used to estimate the effects of adverse selection and moral hazard on yield performance and chemical expenditure for both the natural-

disaster-only and the multi-risk cover insurance. Our results show that insured farmers spend more on chemicals that can be monitored by the insurer, and spend less on the inputs that cannot be monitored compared to if they had not purchased insurance. Since yield depends on both types of inputs (i.e. monitored and non-monitored ones), the final moral hazard effect of insurance on yield is ambiguous. There is also evidence suggesting that farmers with private information that makes them use less chemicals are likely to have true demand for the natural-disaster-only insurance, while those who expect a lower yield are likely to have true demand for the multi-risk insurance.

The rest of the paper is organized as follows. The next Section introduces the background of the Philippines crop insurance market. Our theoretical framework is described in the third Section. The fourth Section describes the data, and the estimation strategy is detailed in the fifth Section. Empirical results are presented and discussed in the sixth Section and the final Section concludes.

Background

The agricultural industry has been recognized by the Philippine 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), weather shock is the major factor that contributes to impoverishment in the Philippines. Farmers could mitigate the impact of 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 suitable during recent years when farmers have been confronted with new 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. 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). 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.

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. However, it should be noted that the PCIC corn insurance product is subject to the following liability ceilings: (a) PHP 40,000/USD 948 per hectare for hybrid and GMO corn varieties, and (2) PHP 28,000/USD 664 per hectare for open-pollinated varieties.

Reyes et al. (2015) points 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 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) 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.

The Philippine government heavily subsidizes corn insurance premiums. The government pays more than 50% of the total insurance premium for corn. Lending institutions also share a portion of the premium if the insured farmer borrows from them (i.e., the borrower client). Therefore, the borrower clients' premiums are shared among the lending institution, the government, and the farmers themselves. The self-financed clients' premiums, on the other hand, are only shared with the government. But note that the total premium rate is typically the same for both the borrowing and the self-financed farmers. In addition, the government's share is also the same for both types of farmers. This arrangement means that self-financed clients have to pay an additional amount of premium (relative to the borrower clients), which is equivalent to what would have been assumed by lending institutions if they were borrower clients.

The premium rate shared by the lending institution and the government is also constant across different types of insurance cover (i.e., natural disaster vs. multi-risk) as well as different risk classifications (i.e., low vs. medium vs. high). This scheme implies that the premium rate paid by the lending institutions and the government remains the same for farmers with different risk classification levels and the additional premium for being high risk will have to be borne by the high-risk farmer themselves. For example, the premium rate (premium as a percentage of liability) paid by a self-financed corn farmer classified as high risk is 11.48% and the government pays 10.62%; while a low risk farmer only pays 5.83% himself with the government still paying 10.62%.

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% 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). One important feature of the Philippine crop insurance program is that during production, insured farmers are monitored by technicians. For farmers who borrow money from official lending institutions and are required to purchase insurance, they receive monitoring from bank technicians, who make sure the loan is not diverted for other purposes and used to purchase inputs according to the stated plan. For those farmers who do not borrow from formal sources, they also need to submit the Farm Plan and Budget to PCIC and agree to place themselves under the technical supervision of PCIC-accredited agricultural production technicians during the growing season. Therefore, for both types of insured farmers, their farming activities are monitored by technicians during the production season.

From 1982 to 1990, the PCIC corn insurance program had a difficult time when the total claim amount consistently exceeded total premium collected. Since 1990, the situation has been reversed and total premiums are now much larger than the indemnities paid. In 2012, the total premium was two times larger than the total indemnities paid out to producers. In addition, the number of insured farmers had declined from the peak at 40,410 in 1990 to 3,910 in 2007. However, after 2007, the number of insured farmers has steadily increased and reached 12,271 in 2012. This growth in participation may be attributed to the increased frequency of natural disasters during that period. As a result, farmers may have had an increasing awareness of the importance of insurance. This

growth in participation may also be ascribed to the promotion of various new largely-subsidized special crop insurance programs during this period. These special programs were officially launched in 2012 (Reyes, Gloria and Mina, 2015).

In 2012, 29% of the insured farmers had indemnities paid from the PCIC corn crop insurance program. As for the causes of loss, typhoons, floods and droughts were the main causes. For example, in 2012, an indemnity of PHP 15.77/USD 0.374 million was paid for losses due to typhoons or floods, while PHP 4.53/USD0.107 million and PHP 6/USD 0.142 million were paid for losses due to pests and diseases, respectively. In general, the losses caused by natural disasters are more than twice the losses caused by pests or diseases (Yorobe and Luis, 2015).Therefore, seasonal climate variability and occurrence of adverse weather events are the main sources of uncertainty for corn farmers in the Philippines.

Theoretical Framework

In this section, we set up a model to illustrate the moral hazard and adverse selection effects in the context of the Philippines crop insurance market. Formally, assume a representative farmer owns one hectare of arable land.[25] The farmer's production technology can be described by the production function $Q(x, y)$, where x is the input that can be monitored under insurance like fertilizer and pesticides, and y is the input that cannot be monitored such as effort. We further assume $Q_x(x, y) > 0, Q_{xx}(x, y) < 0, Q_y(x, y) > 0, Q_{yy}(x, y) < 0$. The model has three stages. In the first stage, the farmer

[25] We fix the size of the land to focus our analysis on the effect of insurance on the intensive margin of input use.

decides which insurance to purchase. This includes no insurance, the natural disaster only insurance and the multi-risk insurance. The insurance is such that if there is a qualified loss, the indemnity payment will be part of the farmer's cost on input x, proportional to his yield loss. In the second stage, conditional on purchasing insurance, the farmer needs to submit a farming plan and budget, stating how much x he plans to use and he will be monitored throughout the production process so that the stated amount is actually used. When x amount of the first input is used, the expected yield for the farmer is $\bar{Q}(x) = \sum p(w)wQ(x,\bar{y})$, where $\bar{y}$ is the average amount of the y input the insurance company expects the farmer to exert and $0 \leq w \leq 1$ is the percentage of yield that will survive the shocks during the production. w is assumed to be random and follows a discrete distribution of $p(w)$. In the final stage, the farmer decides how much y to use. As a result, when it comes to harvest time, the realized yield is $wQ(x,y)$, given the percentage of yield that survives the shocks being w. If the losses are covered by the insurance the farmer purchases in the first stage, the insurance company will pay the farmer $\left(1 - \frac{wQ(x,y)}{\bar{Q}(x)}\right)\alpha x$, where α is the unit price of x. $\left(1 - \frac{wQ(x,y)}{\bar{Q}(x)}\right)$ is the share of expected yield that is lost during production.

The model is solved using backward induction. We first examine the farmer's decision in the third stage. The farmer's expected utility in this stage can be described by the following equation,

(1) $$EU(x,y) = \sum p(w)U\left[wPQ(x^*,y) - \alpha x^* - \beta y + \mathrm{P}_{covered}\left(1 - \frac{wQ(x^*,y)}{\bar{Q}(x^*)}\right)\alpha x^* - P_I\right],$$

where U is a risk-averse utility function ($U' > 0, U'' < 0$), β is the unit cost for y, x^* is the optimal input decision from the second stage, $\mathrm{P}_{covered}$ is the probability that the losses are covered by the insurance purchased and P_I is the insurance premium. Maximizing (1) with respect to y yields the following first order condition,

(2) $$\sum p(w)U'(\cdot)\left[wPQ_y(x^*,y) - \beta - \mathrm{P}_{covered}\frac{wQ_y(x^*,y)}{\bar{Q}(x^*)}\alpha x^*\right] = 0.$$

The second-order sufficient condition for the maximum is

(3) $$\sum p(w)\left\{U''(\cdot)\left[wPQ_y(x^*,y) - \beta - \mathrm{P}_{covered}\frac{wQ_y(x^*,y)}{\bar{Q}(x^*)}\alpha x^*\right]^2 + U'(\cdot)\left[wPQ_{yy}(x^*,y) - \mathrm{P}_{covered}\frac{wQ_{yy}(x^*,y)}{\bar{Q}(x^*)}\alpha x^*\right]\right\} < 0.$$

We denote the solution to (2) as $y^* = y(x^*, \mathrm{P}_{covered})$, which is a function of x^*, $\mathrm{P}_{covered}$ as well as other parameters of the model. The derivative of y^* with respect to $\mathrm{P}_{covered}$ is,

(4) $$\frac{dy^*}{d\mathrm{P}_{covered}} = \frac{\partial y^*}{\partial \mathrm{P}_{covered}} + \frac{\partial y^*}{\partial x^*}\frac{\partial x^*}{\partial \mathrm{P}_{covered}},$$

where $\frac{\partial y^*}{\partial \mathrm{P}_{covered}}$ can be obtained by total differentiation of (2) with respect to y and $\mathrm{P}_{covered}$ and rearranging terms. $\frac{\partial y^*}{\partial x^*}$ can be obtained by total differentiation of (2) with respect to y and x^* and rearranging terms. $\frac{\partial x^*}{\partial \mathrm{P}_{covered}}$ will be obtained from analysis of the second stage decision below. Each term can be either positive or negative, depending on the specific values of parameters. As a result, the effect of $\mathrm{P}_{covered}$ on y^* can be either positive or negative.

In the second stage, the farmer maximizes the following objective function,

(5) $$EU\big(x, y(x)\big) = \sum p(w)U\left[wPQ\big(x, y(x)\big) - \alpha x - \beta y + P_{covered}\left(1 - \frac{wQ\big(x,y(x)\big)}{\bar{Q}(x)}\right)\alpha x - P_I\right].$$

Maximizing (5) with respect to x yields the following first order condition,

(6) $$\sum p(w)U'(\cdot)\left[wP\left[Q_x + Q_y\frac{\partial y}{\partial x}\right] - a - \beta\frac{\partial y}{\partial x} + P_{covered}\left(1 - \frac{wQ(x,y(x))}{\bar{Q}(x)}\right)a + P_{covered}\left(-\frac{w\left(Q_x+Q_y\frac{\partial y}{\partial x}\right)}{\bar{Q}(x)} + \frac{wQ(x,y(x))}{\bar{Q}(x)^2}\bar{Q}_x(x)\right)ax\right]=0.$$

The second-order sufficient condition for the maximum is

$$\sum p(w)\{U''(\cdot)\left[wP\left[Q_x + Q_y\frac{\partial y}{\partial x}\right] - a - \beta\frac{\partial y}{\partial x} + P_{covered}\left(1 - \frac{wQ(x,y(x))}{\bar{Q}(x)}\right)a + P_{covered}\left(-\frac{w\left(Q_x+Q_y\frac{\partial y}{\partial x}\right)}{\bar{Q}(x)} + \frac{wQ(x,y(x))}{\bar{Q}(x)^2}\bar{Q}_x(x)\right)ax\right]^2 + U'(\cdot)\left[wP\left[Q_{xx} + Q_{yx}\frac{\partial y}{\partial x} + Q_y\frac{\partial^2 y}{\partial^2 x}\right] - \beta\frac{\partial^2 y}{\partial^2 x} + 2wP_{covered}\left(-\frac{\left(Q_x+Q_y\frac{\partial y}{\partial x}\right)}{\bar{Q}(x)} + \frac{Q(x,y(x))}{\bar{Q}(x)^2}\bar{Q}_x(x)\right)a + wP_{covered}\left(-\frac{Q_{xx}+Q_{yx}\frac{\partial y}{\partial x}+Q_y\frac{\partial^2 y}{\partial^2 x}}{\bar{Q}(x)} + \frac{\left(Q_x+Q_y\frac{\partial y}{\partial x}\right)}{\bar{Q}(x)^2}\bar{Q}_x(x) + \frac{\left(Q_x+Q_y\frac{\partial y}{\partial x}\right)\bar{Q}_x(x)+Q(x,y(x))\bar{Q}_{xx}(x)}{\bar{Q}(x)^2} - \frac{Q(x,y(x))}{\bar{Q}(x)^3}\bar{Q}_x(x)^2\right)ax\right] < 0 \quad .$$

We denote the solution to (6) as x^*. $\frac{\partial x^*}{\partial \mathrm{P}_{covered}}$ can be obtained by total differentiation of (6) with respect to x and $\mathrm{P}_{covered}$ and rearranging terms. Again, each term can be either positive or negative, depending on the specific values of parameters.

In a standard moral hazard model, we expect that when insurance coverage increases from no coverage to basic only and to multi-risk cover, that is, as $\mathrm{P}_{covered}$ increases, the use of inputs, which is not monitored, will decrease. However, in our model, the use of input x is monitored and this changes the effect of insurance on input use. First,

since the use of input x is monitored, there is no room to engage in moral hazard behavior regarding this input. In this case, when the farmer is insured, his effective unit cost of input x becomes less because when there is a loss, the insurance company will reimburse him part of the input cost. This gives him incentives to use more x. On the other hand, when $\mathrm{P}_{covered}$ changes, the optimal amount of input y used also changes (see (4) above). Since the marginal value of product from using more x, $wP\left[Q_x + Q_y \frac{\partial y}{\partial x}\right]$, depends on y, $\mathrm{P}_{covered}$ also has an effect on the marginal value of product from using more x. Since the effect of $\mathrm{P}_{covered}$ on y and the effect of y on the marginal value of product from using more x are both uncertain (the latter is uncertain because it depends on whether the two inputs are complements or substitutes in the production function), it's possible for $\mathrm{P}_{covered}$ to have a negative effect on the marginal value of product from more x. In this case, this will give the farmer less incentives to use x. Because of these two competing effects, when insurance coverage increases, the farmer could use more or less of the x input.

As (4) shows, the effect of insurance coverage on the amount of input y used is also uncertain. On one hand, since the use of input y cannot be monitored, the farmer can engage in moral hazard. When the farmer is insured, the negative effect of using less input y on the expected return is reduced, thus giving the farmer incentives to use less y. On the other hand, the optimal amount of input y to be used depends on the amount of input x is used. If the use of input x increases and the two inputs are complements, then

there are more incentives to increase the use of y as well. Due to these two competing effects, the final effect of insurance on y is also uncertain.

Finally, in the first stage, the farmer chooses which insurance to purchase. Each insurance comes with a different premium P_I^j and a different coverage level $P_{covered}^j$, where j denotes the insurance plan. If the farmer chooses to not to purchase insurance, then $P_I^j = P_{covered}^j = 0$. The expected utility the farmer obtains from choosing plan j is $EU^j\left(x_j^*, y\left(x_j^*\right)\right)$, where the function EU is defined in (5) and x_j^* and $y\left(x_j^*\right)$ are the optimal input decisions under plan j. The farmer will choose the plan that gives him the largest expected utility. Different farmers have different private information about the risks they are facing, that is, the distribution of the losses $p(w)$ is different for different farmers. As a result, different farmers self-select into different insurance plans. As our model is quite complicated, we cannot prove any adverse selection results. However, we expect that given everything else, those farmers who have private information that they are not likely to suffer from any losses are not going to purchase insurance voluntarily. Those who expect to only suffer from natural disasters will purchase the natural disasters only insurance plan and those who expect to suffer from other risks will purchase the multi-risk cover insurance.

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 for the survey using the multi-stage stratified random sampling approach. Two municipalities from each province were chosen based on the area devoted to corn production and the number of producers enrolled in PCIC corn insurance program. The data on the area devoted to corn and the number of insured producers 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. In each stratum, 213 farmers were chosen randomly. The list of insured corn farmers was provided by PCIC and the list of non-insured farmers were obtained from village heads. A total of 426 corn producers were surveyed.

A few farmers were dropped from the sample. First, two farmers who used open-pollinated seeds were dropped. It is because the yields of open-pollinated seeds are usually lower and farmers who use this type of seeds may behave quite differently from farmers who purchase seeds. Second, 20 farmers who were paid care-takers of the fieldswere dropped because they usually do not make insurance purchase and input use decisions. Finally, some farmers reported unrealistically high per hectare yields and these numbers were likely due to measurement errors. Thus, considering the average mean yield is just five thousand kilograms per hectare, six farmers with historical mean yields

larger than 12,000kg per hectare plus 18 farmers with missing historical yields were dropped from this sample. As a result, there are 380 farmers in our working sample.

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 indicators of cognitive ability and cautiousness). In particular, the survey asked whether the farmer had crop insurance and whether the farmer would have bought insurance if it was not required. We divide farmers into three groups based on their responses to these two questions. Among insured farmers, those in group VOLUNTARY stated that they voluntarily chose to purchase insurance and would have purchased it even if it was not required. Farmers in group FORCED are those who were forced to purchase insurance and would have not done so if it was not required. Farmers in the third group, group NO, had the option to purchase insurance but chose not to do so.

Empirical Strategy

We adopt the empirical strategy of Liu, Vukina and Nestic (2012) to estimate the moral hazard and adverse selection effects of crop insurance. Specifically, we can write a farmer's outcome variable Y_i as a function of a constant c, his or her insurance status I_i, a set of observed characteristics X_i, unobserved heterogeneity a_i and some noise ε_i with mean zero,

(7) $$Y_i = c + \alpha I_i + \beta X_i + a_i + \varepsilon_i.$$

Obviously, in this specification, α captures the effect of moral hazard.

Identification

From (7), it is clear that the average outcome difference between group FORCED and group NO is the following,

(8) $$E[Y|X, FORCED\ ] - E[Y|X, NO\ ] = \alpha + \{E(a_i|X, FORCED) - E(a_i|X, NO)\}.$$

If conditional on observables, the average farmer unobserved heterogeneity is the same for group FORCED and group NO, that is, $E(a_i|X, FORCED) = E(a_i|X, NO)$, then the average outcome difference between the two groups $E[Y|X, FORCED\ ] - E[Y|X, NO\ ]$ provides an unbiased estimate of the moral hazard effect of crop insurance α. If $E(a_i|X, FORCED) > E(a_i|X, NO)$, which means on average the unobserved heterogeneity in group FORCED is larger than that of group NO, then the moral hazard effect would be overestimated. Finally, if $E(a_i|X, FORCED) < E(a_i|X, NO)$, then the moral hazard effect would be underestimated.

We believe the assumption that $E(a_i|X, FORCED) = E(a_i|X, NO)$ is a mild and reasonable one in our context. Farmers in group FORCED and group NO are the same in the sense that both types do not have real demand for crop insurance. They differ as farmers in the group FORCED are required to purchase crop insurance by their creditors. This implies that farmers in group NO have more favorable financial stance than farmers in group FORCED. The reasons for a farmer to have worse financial situation could be either he/she has little wealth or he/she had a bad harvest in previous years. In our matching estimation below, we control for a farmer's wealth and previous performance using variables such as the size of the farm and the farmer's historical yields. We believe

that conditional on these observables, the assumption that the average unobserved farmer heterogeneity is the same across the two groups is likely to hold.

Equation (7) also implies that the average outcome difference between group VOLUNTARY and group FORCED is,

(9) $$E[Y|X, VOLUNTARY] - E[Y|X, FORCED] = E(a_i|X, VOLUNTARY) - E(a_i|X, FORCED).$$

The true selection effect is the difference in average farmer unobserved heterogeneity between farmers who have real demand for crop insurance (those in group VOLUNTARY) and those who do not have real demand for crop insurance (those in groups FORCED and NO), that is,

$\gamma = E(a_i|X, VOLUNTARY) - E(a_i|X, FORCED\ and\ NO)$. Under the same assumption above, that is, $E(a_i|X, FORCED) = E(a_i|X, NO)$, we have $E(a_i|X, FORCED) = E(a_i|X, FORCED\ and\ NO)$. As a result, the average outcome difference between the two groups $E[Y|X, VOLUNTARY\ ] - E[Y|X, FORCED\ ]$ provides an unbiased estimate of the adverse selection effect of crop insurance γ. But again, if this assumption does not hold, then the adverse selection effect would be either underestimated or overestimated.

Matching Estimation

The empirical estimation of moral hazard and adverse selection effects is carried out based on equations (8) and (9) by the use of the propensity score matching (PSM) method (e.g. Rosenbaum and Rubin, 1983). We perform four matching estimations: the moral hazard effect of the natural-disaster-only insurance, the moral hazard effect of the multi-

risk insurance, the adverse selection into the natural-disaster-only insurance and the adverse selection into the multi-risk insurance.

Under the assumption $E(a_i|X, FORCED) = E(a_i|X, NO)$, (8) implies a consistent estimator for the average moral hazard effect for farmers in FORCED and NO groups is

(10) $$\hat{\alpha} = \frac{1}{N_1}\sum_{i=1}^{N_1}(\hat{Y}_{i1} - \hat{Y}_{i0}),$$

where N_1 is the number of farmers in FORCED and NO groups. If i is a farmer in the FORCED group, $\hat{Y}_{i1} = Y_i$ and $\hat{Y}_{i0} = Y_{h(i)}$ where farmer $h(i)$ is in the NO group and is closest to farmer i in terms of their propensity score. Similarly, if i is a farmer in the NO group, $\hat{Y}_{i0} = Y_i$ and $\hat{Y}_{i1} = Y_{h(i)}$ where farmer $h(i)$ is in the FORCED group and is closest to farmer i in terms of their propensity score. We can also estimate the average moral hazard effect for farmers in the two groups separately. The average moral hazard effect for farmers in the FORCED group can be estimated using,

(11) $$\hat{\alpha}_{FORCED} = \frac{1}{N_{11}}\sum_{i=1}^{N_{11}}(Y_i - \hat{Y}_{i0}),$$

where N_{11} is the number of farmers in the FORCED group and $\hat{Y}_{i0}$ is defined above. The average (counterfactual) moral hazard effect for farmers in the NO group can be estimated using,

(12) $$\hat{\alpha}_{NO} = \frac{1}{N_{12}}\sum_{i=1}^{N_{12}}(\hat{Y}_{i1} - Y_i),$$

where N_{12} is the number of farmers in the NO group and $\hat{Y}_{i1}$ is defined above.

As for adverse selection, again under the assumption $E(a_i|X, FORCED) = E(a_i|X, NO)$, (9) implies a consistent estimator for the average adverse selection effect is

(13) $$\hat{\gamma} = \frac{1}{N_2}\sum_{i=1}^{N_2}(\hat{Y}_{i1} - \hat{Y}_{i0}),$$

where N_2 is the number of farmers in VOLUNTARY and FORCED groups. If i is a farmer in the VOLUNTARY group, $\hat{Y}_{i1} = Y_i$ and $\hat{Y}_{i0} = Y_{h(i)}$ where farmer $h(i)$ is in the FORCED group and is closest to farmer i in terms of their propensity score. Similarly, if i is a farmer in the FORCED group, $\hat{Y}_{i0} = Y_i$ and $\hat{Y}_{i1} = Y_{h(i)}$ where farmer $h(i)$ is in the VOLUNTARY group and is closest to farmer i in terms of their propensity score. We can also estimate the average adverse selection effect for farmers in the two groups separately. The average adverse selection effect for farmers in the VOLUNTRAY group can be estimated using,

(14) $$\hat{\gamma}_{VOLUNTARY} = \frac{1}{N_{21}} \sum_{i=1}^{N_1} (Y_i - \hat{Y}_{i0}),$$

where N_{21} is the number of farmers in the VOLUNTRAYR group and $\hat{Y}_{i0}$ is defined above. The average (counterfactual) adverse selection effect for farmers in the FORCED group can be estimated using,

(15) $$\hat{\gamma}_{FORCED} = \frac{1}{N_{22}} \sum_{i=1}^{N_{22}} (\hat{Y}_{i1} - Y_i),$$

where N_{22} is the number of farmers in the FORCED group and $\hat{Y}_{i1}$ is defined above.

Variables

In our analysis, we focus on two outcome (Y) variables: farmer i's yield ($Yield_i$) and his total expenditure on chemical use ($Expenditure_i$). Many studies in the litreature focus on these two variables when studying moral hazard and adverse selection effects in the context of crop insurance (see Smith and Goodwin (1996) on chemical use, and Quiggin, Karagiannis, Stanton (1993) on production). Also, as discussed above, we need to control

for a set of observed farm/farmer characteristics X_i in matching estimations. These variables are determinants of the outcome variables and controlling for them makes out assumption $E(a_i|X, FORCED) = E(a_i|X, NO)$ more likely to hold. Below we discuss each of the control variables in turn.

Since each farmer has land with different quality, faces different weather conditions, and uses different technology, we include the average yield per hectare of the two most recent years, that is, 2010 and 2011, ($HistoricalYield_i$) in the regressions to control for the effect of unobserved individual heterogeneity that are not captured by the province dummies on input use.26 In addition, lagged yield is a key determinant of the current yield because farming conditions are persistent across years.

A cognitive ability variable is also included as a control variable. This variable was collected using a word recall approach. Each respondent was asked to repeat a list of ten words for two times, after listening to those words. One was at the beginning and the other was 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 ($Cognitive_i$). Farmers with high cognitive ability tend to be more productive and that will certainly affect his input use decisions.

Males and females are different both physically and psychologically, so the gender of the farm household's head (sex_i) can cause differences in many aspects including yield and input use. Older farmers are more experienced in farming and more confident in coping with farming risks, which can in turn influence yield and input use

[26] For those respondents who could not recall the yields of these two years, the values for this variable are denoted as missing.

decisoons. This is why age (age_i) is included as a control variable. Household size (hs_i) eis another variable inclued. Families with babies and old people may not be very productive. Also, families with many children need to pay for kids' tuition and may spend less on inputs. More years of education ($Education_i$) could make a farmer more receptive to new farming techniques and hence more productive. It also can influence his input use decision. This is the reason why education is included as another control variable.

Different topography features of the planted field determine the field's humidity level and how much sunshine it receives and hence influence yield and the input use decisons. For this reason, we control for the topography dummy variable $Flat_i$, which equals 1 if farmer i reported that his or her land is plain/flat, rolling or hilly, and equals 0 if mountainous. .

Yield and input decisions also depend on the type of seeds used. The $Hybrid_i$ variable is equal to 1 if farmer i uses hybrid seeds and 0 if GMO or BT seeds are used. Newly developed GMO and BT seeds offer various new features, such as inherent resistance to pests such Asian corn borers so less pesticides will be used and herbicide tolerance so that farmers can apply more weedicides without damaging the plant.

The variable $DistanceRoad_i$ is the distance between farmer i's fields and the nearest road. Better access allows farmers to take better care of their fields (e.g. applying pesticides more frequenctly). As a result, yields are likely to be higher.

The total farming area is denoted as $Area_i$. It is expected that farmers with larger fields are more wealthy and this variable is included to capture the wealth effects on input

use and yield. This variable also captures the effect of scale on yield and input use. Two variables are used to control for farms' diversification. $OtherCrop_i$ 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 raises livestock tell how diversified the farm is. A specialized farmer in corn production might be more productive due to specialization. On the other hand, farmers who also raise livestock can apply livestock manure to their fields in stead of using fertilizers.

A risk aversion measure ($RiskAverse_i$) is also included as a control variable. Farmers' risk preference is measured by a hypothetical question asking whether they are willing to try a new seed variety that may double their yield or cut their yield by several given proportions (20%, 50% and 75%). Those farmers who are not willing to try this risky seed even when it has only half chance of decreasing their yields by 20% are considered to be the most risk-averse ones, and $RiskAverse_i$ is set to be 1 for these farmers. The variable takes the value of 0 for other farmers. Risk aversion affects yield performance and input use because risk-averse farmers may use the most conservative approach such as using more chemicals to minimize uncertainty in their farming income.

Finally, province dummies are included to control for heterogeneity in weather, chemical prices or any other effects that vary at the regional levels. All the variables discussed in this section, together with their definitions, are listed in Table 3.1. The summary statistics for these variables are reported in Table 3.2 by group and insurance type.

Estimation Results

The first step in propensity score matching estimation is to compute the propensity scores. To do so, we estimate a Logit model for each matching estimation and the propensity score for a farmer is the predicted probability for him/her being in the treated group. The Logit estimation results for all four matching estimations are collected in Table 3.3. The distributions of the computed propensity scores by matching estimation and group are plotted in Figure 3.1.

Our main results, the average moral hazard and adverse selection effects, are presented in Table 3.4. First, insurance is found to have a positive effect on chemical expenditure. Having the natural-disaster-only cover increases the expenditure on chemicals by 1,580 PhP per hectare, while having the multi-risk cover increase the expenditure by 2,053 PhP per hectare. Both results are statistically significant. This finding implies that basing indemnity payments on observable input costs and combining it with monitoring successfully motivate farmers to make more investment in farming. In addition, the result that the mulit-risk cover has a larger effect on chemical use than the natural-disaster-only cover implies that more comprehensive protection from risks provides farmers with larger incentives to devote their resources to farming.

Second, it is found that the natural-disaster-only cover insurance decreases the yield by 926.6 kilograms per hectare and this effect is statistically significant, while the multi-risk cover insurance has a positive but insignificant effect on yield. This finding implies that insurance has a negative effect on effort or other unobservable inputs, As effort is unobservable and hard to monitor, farmers exert less effort when they have

insurance. Since the moral hazard effect of insurance on yield depends on both its effect on chemical expenditure, which is found to be positive, and on its effect on effort, which is neagive, the final effect on yield can either be negative or positive.

Turning to adverse selection, our results show that farmers who tend to use less chemicals self-select into the natural disaster cover only insurance, but there is no such evideicne for selection into the multi-risk cover insurance. This finding implies that some farmers possess private knowledge regarding whether their fields will suffer from losses due to pests and other plant diseases. Those farmers who believe their fields are not likely to suffer from such risks spend less on chemicals and purchase natural-disaster-only insurance.

Finally, our results also show that farmers who expect a lower yield do not self-select into the natural-disaster-only insurance, but there is some evidence that they self-select into the multi-risk cover insurance. The latter result is significant at 11.5%. Those farmers who self-select into the multi-risk insurance have a yield 454.7 kilograms per hectare less than other farmers on average. This finding is consistent with our hypothesis above, that is, farmers do not possess private knowledge regarding how likely their fields will suffer from natural disasters, but have some private information regarding the risks covered by the multi-risk insurance.

Robustness Checks

One important assumption underlying the propensity score matching estimation above is the overlapping condition, which means for any farmer, we can find another farmer in the

other group that has a very similar propensity score. Figure 1 plots the distributions of the estimated propensity scores for all the farmers in our dataset by group and matching estimation. For the two estimations for moral hazard (Figure 3.1 and 3.3), we find that for each farmer in the NO group, we can find a farmer in the FORCED group with very similar propensity score. But for some farmers in the FORCED group, there are no farmers in the NO group that have a similar propensity score. This implies that the overlapping condition holds better for farmers in the NO group. Therefore, in our robustness check, we repeat the same propensity score matching estimation only for farmers in the NO group and the results are collected in the left column of Table 3.5. The results are very similar to our main results in Table 3.4, both in terms of the signs and magnitudes of the moral hazard effects as well as their statistical significance.

Similarly, Figure 3.2 and 3.4 show that the overlapping condition is more likely to hold for farmers in the VOLUTARY group in the matching estimation for the adverse selection effects. We therefore repeat the estimation of the adverse selection effects for farmers in the VOLUNTARY group only. Results are reported in the second column of Table 3.5. Again, results are very similar to our main results in Table 3.4.

Conclusion

In this paper, using a survey question that elicits farmers' true preference for corn insurance, we separately identify and estimate the moral hazard and adverse selection effects of crop insurance on famers' yield and chemical expenditure for both the natural-disaster-only insurance as well as the multi-risk cover insurance. We find that when

spending on chemicals can be monitored by the insurer, farmers spend moreonce they have insurance and use less of the inputs that cannot be monitored (i.e. effort). Since yield depends on both types of inputs, the final moral hazard effect of insurance on yield is ambiguous. We also find some evidence that farmers who expect to use less chemicals self-select into the natural-disaster-only insurance and those expect a lower yield self-select into the multi-risk insurance.

Our analysis provides valuable information for the improvement of crop insurance programs in the Phillippines as well as for other countries, especially those where crop insurance programs have become too expensive due to moral hazard and adverse selection. Our results show that the moral hazard problem can be curbed by mechanisms such as monitoring. However, we need to caution that monitoring is only effective in combating certain kinds of moral hazard behavior. Our results also suggest that previous studies that focus on the moral hazard effect of insurance on chemical use might give us an incomplete picture of the moral hazard problem in crop insurance. Moral hazard could arise not only because farmers use less checmicals during the season, but also because they exert less effort.

Our adverse selection results suggest several ways to improve the Phillipines crop insurance program. First, the fact that farmers who tend to use less chemicals self-select into the natural diasaster cover only insurance implies that the insurer could impose a minimum amount of chemicals that must be applied for purchasers of this type of insurance and monitor this throughout the production season. Second, the result that farmers who expect a lower yield self-select into the multi-risk cover insurance suggests

that the insurer should take the expected yield into account when setting the premium rate rather than varying the premium rate only by region.

REFERENCES

Fang, H., M. P. Keane, and D. Silverman. 2008. “Sources of Advantageous Selection: Evidence from the Medigap Insurance Market.” *Journal of Political Economy* 116(2): 303-348.

Finkelstein, A. and K. McGarry. 2006. “Multiple Dimensions of Private Information: Evidence from the Long-Term Care Insurance Market.” *The American Economic Review* 96 (4) : 938-958.

Garrido, C. A., and D. Zilberman. 2007. “Revisiting the demand of agricultural insurance: the case of Spain.” *Agricultural Finance Review*: 43-66.

Goodwin, B. 1993. "An Empirical Analysis of the Demand for Multiple Peril Crop Insurance." *American Journal of Agricultural Economics* 75: 425-434.

Gunnsteinsson, S. 2014. “Experimental Identification of Asymmetric Information: Theory and Evidence on Crop Insurance in the Philippines.” Working paper.

Hou, L., D. L. Hoag, and Y. Mu. 2011. “Testing for adverse selection of crop insurance in northern China.” *China Agricultural Economic Review* 3(4): 462-475.

Just, R. E., L. Calvin, and J. Quiggin. 1999. “Adverse selection in crop insurance: Actuarial and asymmetric information incentives.” *American Journal of Agricultural Economics* 81(4): 834-849.

Knight, T. O., and K. H. Coble. 1997. “Survey of US multiple peril crop insurance literature since 1980.” *Review of Agricultural Economics* 19(1): 128-156.

Liu, X., Nestic, D., and Vukina, T. 2012. "Estimating Adverse Selection And Moral Hazard Effects With Hospital Invoices Data In A Government ‐ Controlled Healthcare System." *Health economics* 21(8): 883-901.

Makki, S. S., and A. Somwaru. 2001. "Evidence of Adverse Selection in Crop Insurance Markets." *Journal of Risk and Insurance* 68 (4): 685-708.

Quiggin, J., G. Karagiannis, and J. Stanton. 1993. "Crop Insurance and Crop Production: An Empirical Analysis Study of Moral Hazard and Adverse Selection." *Australian Journal of Agricultural Economics* 37 (2): 95-113.

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. T*argeting the Agricultural Poor: The Case of PCICs Special Programs*. Makati, Philippines: Philippine Institute for Development Studies, No. DP 2015-08, January.

Roberts, M. J., N. Key, and E. O'Donoghue. 2006. "Estimating the extent of moral hazard in crop insurance using administrative data." *Review of Agricultural Economics*: 381-390.

Rosenbaum, P. R., and Rubin, D. B. 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika* 70(1): 41-55.

Smith, V. H., and A. E. Baquet. 1996. "The demand for multiple peril crop insurance: evidence from Montana wheat farms." *American journal of agricultural economics* 78(1): 189-201.

Smith, V. H., and B. K. Goodwin. 1996. "Crop insurance, moral hazard, and agricultural chemical use." *American Journal of Agricultural Economics* 78(2): 428-438.

Table 3.1. List of Variables

Variable	**Unit**	**Definition**
Dependent variables		
Yield	1,000 kg/hectare	Yield of the largest parcel per hectare in 2012
Expenditure	10,000 PHP	Total expenditure on chemical inputs
Independent variables		
HistoricalYield	1,000 kg/hectare	Mean yield per hectare of 2010 and 2011
Cognitive	Number of words	Number of words recalled from 20 words read to the farmer
Sex		1=male and 0 otherwise
Age	Year	Age of the head in the farming household
Hs	Person	Number of persons in the farming household
Education	Year	Number of years in school
Flat		1=land is plain or flat or rolling and 0 otherwise
Hybrid		1=hybrid seeds and 0 otherwise
DistanceRoad	Kilometer	Distance to the nearest road
Area	Hectare	Total area of planted fields
Livestock		1=farmer raises any livestock and 0 otherwise
OtherCrop		1=farmer plants other crops besides corn and 0 otherwise
RiskAverse		1= most risk-averse farmer and 0 otherwise
Isabella		1=Isabela and 0 otherwise
Pangasinan		1=Pangasinan and 0 otherwise

Table 3.2 Summary Statistics

Panel A: Natural Disaster Cover										
	FORCED					**VOLUNTARY**				
Variable	**Obs**	**Mean**	**Std**	**Min**	**Max**	**Obs**	**Mean**	**Std**	**Min**	**Max**
Yield	48	6.15	3.35	1.25	15.00	38	6.04	2.46	1.50	13.89
Expenditure	48	1.19	0.38	0.37	2.57	38	1.13	0.28	0.54	1.86
HistoricalYield	48	5.43	2.53	1.55	12.00	38	4.78	2.14	0.00	9.15
Cognitive	48	7.21	3.31	1.00	15.00	38	5.87	3.37	2.00	19.00
Sex	48	0.71	0.46	0.00	1.00	38	0.82	0.39	0.00	1.00
Age	47	43.17	10.96	23.00	72.00	38	48.76	12.26	25.00	75.00
Hs	48	4.69	1.48	2.00	9.00	38	4.74	1.50	2.00	9.00
Education	48	8.85	3.31	1.00	15.00	38	8.45	3.55	2.00	18.00
Flat	35	0.91	0.28	0.00	1.00	34	0.97	0.17	0.00	1.00
Hybrid	48	0.60	0.49	0.00	1.00	38	0.76	0.43	0.00	1.00
DistanceRoad	46	1.35	2.35	0.00	12.00	37	0.95	1.33	0.00	5.00
Area	48	2.08	1.83	0.25	8.00	35	2.17	1.64	0.25	8.00
OtherCrop	48	0.44	0.50	0.00	1.00	38	0.50	0.51	0.00	1.00
Livestock	48	0.17	0.38	0.00	1.00	38	0.16	0.37	0.00	1.00
RiskAverse	48	0.19	0.39	0.00	1.00	38	0.08	0.27	0.00	1.00
Isabella	48	0.58	0.50	0.00	1.00	38	0.55	0.50	0.00	1.00
Pangasinan	48	0.21	0.41	0.00	1.00	38	0.34	0.48	0.00	1.00
Panel B: Multi-Risk Cover										
	FORCED					**VOLUNTARY**				
Yield	55	4.46	2.76	0.40	11.20	44	6.38	3.06	0.00	11.67
Expenditure	55	1.29	0.32	0.43	2.06	44	1.30	0.37	0.19	2.26
HistoricalYield	55	4.72	1.81	1.75	8.50	44	5.92	2.43	1.25	11.41
Cognitive	55	9.38	3.36	4.00	20.00	44	8.27	4.13	1.00	19.00
Sex	54	0.59	0.50	0.00	1.00	44	0.61	0.49	0.00	1.00
Age	54	46.52	9.42	30.00	72.00	44	46.09	10.50	25.00	68.00
Hs	55	4.84	1.58	2.00	8.00	44	4.39	1.65	2.00	9.00
Education	55	8.78	3.40	3.00	16.00	44	9.89	3.43	3.00	16.00
Flat	53	0.92	0.27	0.00	1.00	43	0.98	0.15	0.00	1.00
Hybrid	55	0.75	0.44	0.00	1.00	44	0.80	0.41	0.00	1.00
DistanceRoad	53	1.36	3.11	0.00	20.00	43	0.91	1.32	0.00	5.00
Area	54	2.95	3.44	0.50	26.00	44	3.11	1.84	0.50	8.60

Table 3.2 (continued)

OtherCrop	55	0.53	0.50	0.00	1.00	44	0.68	0.47	0.00	1.00
Livestock	55	0.25	0.44	0.00	1.00	44	0.14	0.35	0.00	1.00
RiskAverse	55	0.11	0.31	0.00	1.00	44	0.25	0.44	0.00	1.00
Isabella	55	0.11	0.31	0.00	1.00	44	0.09	0.29	0.00	1.00
Pangasinan	55	0.22	0.42	0.00	1.00	44	0.61	0.49	0.00	1.00
Panel C: No Insurance										
Yield	185	5.52	2.73	0.40	14.55					
Expenditure	185	1.13	0.37	0.23	2.24					
HistoricalYield	185	4.68	2.08	0.53	10.25					
Cognitive	184	6.92	3.12	0.00	16.00					
Sex	185	0.73	0.45	0.00	1.00					
Age	185	49.15	12.18	23.00	77.00					
Hs	185	4.58	1.74	1.00	9.00					
Education	184	8.20	2.94	0.00	14.00					
Flat	184	0.92	0.27	0.00	1.00					
Hybrid	185	0.70	0.46	0.00	1.00					
DistanceRoad	183	0.82	1.29	0.00	6.00					
Area	183	2.37	2.33	0.25	14.40					
OtherCrop	185	0.52	0.50	0.00	1.00					
Livestock	185	0.13	0.34	0.00	1.00					
RiskAverse	185	0.22	0.42	0.00	1.00					
Isabella	185	0.37	0.48	0.00	1.00					
Pangasinan	185	0.30	0.46	0.00	1.00					

Table 3.3 Logistic Regression

	Natural Disaster Cover				Multi-Risk Cover			
	Moral Hazard		Adverse Selection		Moral Hazard		Adverse Selection	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
HistoricalYield	0.2599***	0.11	-0.2511	0.17	0.0040	0.10	0.1221	0.14
Cognitive	-0.0267	0.08	-0.2723	0.18	0.1779**	0.08	-0.0841	0.08
Sex	-0.5114	0.46	3.4642***	1.28	-1.3022	0.43	-0.0325	0.55
Age	-0.0324*	0.02	0.1026**	0.05	0.0039	0.02	-0.0371	0.03
Hs	0.1080	0.13	0.4836	0.34	-0.0470	0.12	-0.0500	0.18
Education	0.0700	0.08	0.2973	0.19	0.1233*	0.07	0.0189	0.09
Flat	-0.3899	0.84	2.3511	1.71	0.4710	0.83	1.6795	1.43
Hybrid	0.2187	0.48	0.3230	0.87	0.2123	0.46	0.3884	0.70
DistanceRoad	0.1986*	0.11	-0.6481**	0.28	0.0702	0.10	0.0140	0.12
Area	-0.0110	0.10	0.4232*	0.26	-0.0408	0.07	0.0080	0.10
OtherCrop	0.8622*	0.53	-2.3374**	1.08	-0.5346	0.44	0.1426	0.69
Livestock	0.0146	0.57	-0.2164	1.13	0.9529**	0.50	-0.1298	0.69
RiskAverse	-0.1792	0.55	-3.3474**	1.66	-1.2687**	0.58	0.6078	0.72
Isabella	0.6739	0.62	0.4930	1.22	-2.5229***	0.70	0.6818	1.01
Pangasinan	-0.7264	0.71	1.1454	1.28	-0.4209	0.62	1.2731*	0.76
_cons	-2.6254	2.02	-10.8087**	5.72	-2.5998	1.72	-0.9566	2.71
Pseudo R2	0.1252		0.3513		0.2383		0.1737	
N	210		62		227		91	

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 3.4 Estimation Results

	Moral Hazard				**Adverse Selection**			
Average Treatment Effect	**Coef.**	**Std. Err.**	**z**	**P>z**	**Coef.**	**Std. Err.**	**z**	**P>z**
Panel A: Natual Disaster Cover								
Expenditure	0.1580**	0.08	2.03	0.0430	-0.1201***	0.05	-2.63	0.0080
Yield	-0.9266***	0.30	-3.09	0.0020	0.1667	0.67	0.25	0.8050
N. of Obs.	210				62			
Panel B: Multi-risk Cover								
Expenditure	0.2053***	0.05	3.98	0.0000	-0.0112	0.11	-0.1	0.9220
Yield	0.2859	0.51	0.56	0.5750	-0.4547	0.29	-1.57	0.1150
N. of Obs.	227				91			

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

Table 3.5 Propensity Score Matching Estimates

	Moral Hazard Effect on NO group				Adverse Selection Effect on FORCED group			
	Coef.	Std. Err.	z	P>z	Coef.	Std. Err.	z	P>z
Panel A: Natural Disaster Cover								
Chemical Expenditure	0.1876**	0.10	1.83	0.067	-0.1844**	0.09	-2	0.046
Yield	-1.1226***	0.37	-3.02	0.002	0.7895	0.50	1.57	0.117
N. of Obs.	210				62			
Panel B: Multi-risk Cover								
Chemical Expenditure	0.1945***	0.06	3.27	0.001	-0.1159	0.10	-1.12	0.262
Yield	0.6175	0.69	0.89	0.372	-0.3324	0.33	-1.02	0.31
N. of Obs.	227				91			

Note: ***, **, and * indicate significant at 1 percent, 5 percent, and 10 percent.

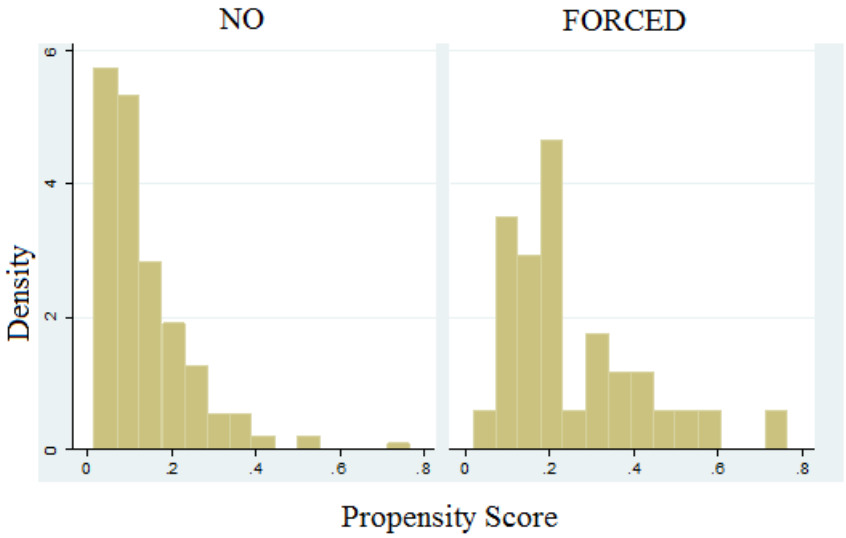

Figure 3.1 Histograms for Estimating Moral Hazard under Natural Disaster Cover

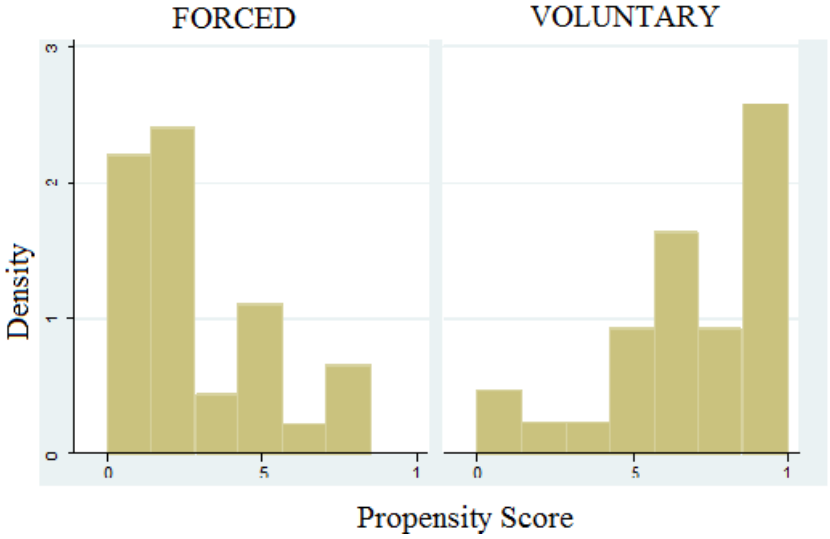

Figure 3.2 Histograms for Estimating Adverse Selection under Natural Disaster Cover

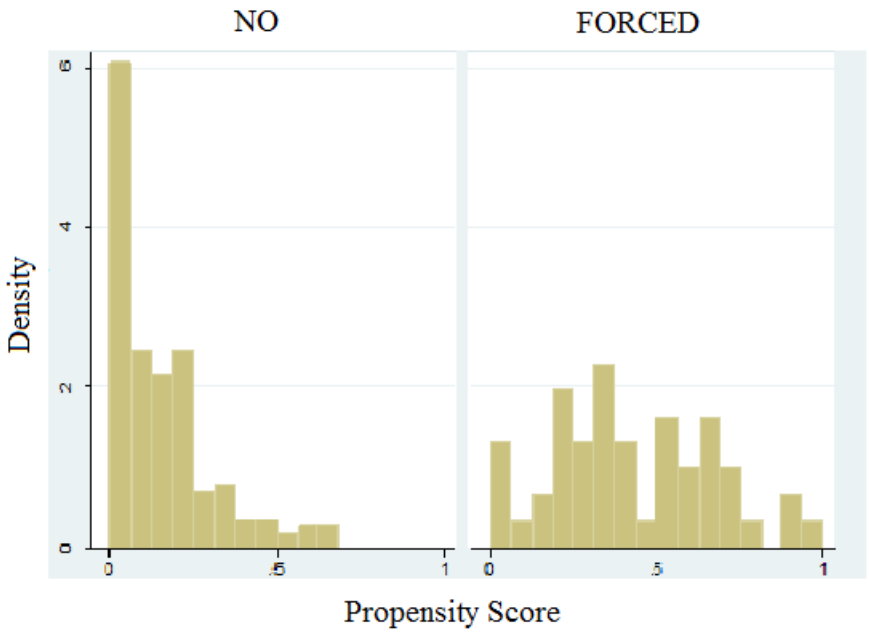

Figure 3.3 Histograms for Estimating Moral Hazard under Multi-Risk Cover

Figure 3.4 Histograms for Estimating Adverse Selection under Multi-Risk Cover

APPENDICES

Appendix A The proof of partial coverage for Chapter 1

The proof for an insurance model with partial coverage is very similar to that for the model with full coverage. Only sketch is provided here.

With partial coverage, the expected utility under insurance becomes,

$$EUI_i(w_0) = p_i U(w_0 - y) + (1 - p_i) U(w_0 + \lambda y - L),$$

where y is the premium and insurer pays $(\lambda + 1)y$ when risks occur. Note the premium rate is 1/($\lambda + 1$). Therefore, the threshold $\bar{p}$ satisfies the following equation,

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

To prove $\bar{p}_C > \bar{p}_B$, it's equivalent to prove $\frac{\bar{p}_C}{1-\bar{p}_C} > \frac{\bar{p}_B}{1-\bar{p}_B}$. Hence, we need to show

$$\frac{U(w_0 + \lambda y - L) - U(w_0 - L)}{U(w_0) - U(w_0 - y)} > \frac{U(w_0 + \alpha + \lambda y - L) - U(w_0 - L + \alpha)}{U(w_0 + \alpha) - U(w_0 - y + \alpha)}.$$

Firstly, we show this inequality works when α changes incrementally. For a small α,

$$\frac{U(w_0 + \lambda y - L) - U(w_0 - L)}{U(w_0) - U(w_0 - y)}$$

$$> \frac{U(w_0 + \lambda y - L) - U(w_0 - L) + \alpha[U'(w_0 + \lambda y - L) - U'(w_0 - L)]}{U(w_0) - U(w_0 - y) + \alpha[U'(w_0) - U'(w_0 - y)]}.$$

It is equivalent to,

$$\frac{U(w_0 + \lambda y - L) - U(w_0 - L)}{U(w_0) - U(w_0 - y)} < \frac{U'(w_0 + \lambda y - L) - U'(w_0 - L)}{U'(w_0) - U'(w_0 - y)}.$$

Since y is small, we need to show ,

$$\frac{U(w_0+\lambda y-L)-U(w_0-L)}{U'(w_0+\lambda y-L)-U'(w_0-L)}>\frac{U'(w_0)}{U''(w_0)}.$$

Then, consider $\lambda y-L$ have an incremental subtraction of y and write

$$\frac{U(w_0+\lambda y-L)-U(w_0-L)}{U'(w_0+\lambda y-L)-U'(w_0-L)}$$

$$=\frac{U(w_0+\lambda y-L)-U(w_0+(\lambda-1)y-L)+U(w_0+(\lambda-1)y-L)-\cdots-U(w_0-L)}{U'(w_0+\lambda y-L)-U'(w_0+(\lambda-1)y-L)+U'(w_0+(\lambda-1)y-L)\ldots-U'(w_0-L)}.$$

Since $-\frac{U''}{U'}$ is a decreasing function, we know,

$$\frac{U'(w_0+\theta y-L)}{U''(w_0+\theta y-L)}>\frac{U'(w_0)}{U''(w_0)},\theta=\lambda,\lambda-1,\ldots 0,$$

as long as $\lambda y-L<0$. This condition is held by construction, because the model is for partial coverage. Similarly to the procedure in the main text, we can show

$$\frac{U(w_0+\lambda y-L)-U(w_0-L)}{U'(w_0+\lambda y-L)-U'(w_0-L)}>\frac{U'(w_0)}{U''(w_0)}.$$

This completes the sketch of the proof.