# Moral Hazard and Adverse Selection Effects of Cost-of-Production Crop Insurance: Evidence from the Philippines

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ABSTRACT

This article aims to theoretically and empirically examine the moral hazard and adverse selection effects of cost-of-production (COP) crop insurance products. Building on existing crop insurance models of moral hazard, as well as a survey-based data set that allows us to separately identify moral hazard from adverse selection, we find evidence that farmers insured under such a COP contract spend more on chemical fertilizers and pesticides (i.e., those inputs whose costs determine the indemnity payments). However, these same COP insured farmers are still likely to use less of the inputs (like effort) whose costs do not enter the indemnity payment formula. Since yield depends on both types of inputs (i.e. the determinants and non-determinants of the indemnity payments), the final moral hazard effect of COP insurance on yields is ambiguous. Our analysis also suggests that farmers who tend to spend less on chemical fertilizers and pesticides are the ones with private information on soil conditions and pest incidence, such that these are the types of farmers who adversely select into COP contracts that only cover weather-related losses.

**Keywords:** *Crop Insurance; Moral Hazard; Adverse Selection*

**JEL Classifications:** Q18; Q12; D82

# Moral Hazard and Adverse Selection Effects of Cost-of-Production Crop Insurance: Evidence from the Philippines

## Introduction

Over the last three decades, crop insurance has played an important risk management role in agricultural production worldwide. Crop insurance helps stabilize farmer incomes over time and also reduces the cost of risk-bearing. Crop insurance is also arguably more important in developing countries (such as the Philippines), where the agricultural sector typically still accounts for a large share of Gross Domestic Product (GDP) and small-scale producers still comprise a significant proportion of the farming population. In this context, crop failures possibly have more serious and disruptive impacts on the rural and/or national economies of developing countries (than in more developed ones). This is one of the reasons why designing, promoting, and maintaining a healthy crop insurance program has been a top agricultural agenda in many developing countries in recent years.

However, asymmetric information problems such as moral hazard and adverse selection have always been a concern for crop insurance, since these issues could undermine the health and continued sustainability of these programs. Moral hazard occurs when insured farmers worry less about the likelihood of a loss (i.e., due to the insurance coverage), take less care of their fields (i.e., use less inputs than is recommended) and, consequently, are more likely to experience a loss (that is not commensurate with the premiums collected). On the other hand, adverse selection arises because high-risk farmers are more likely to purchase crop insurance as they perceive larger benefits from participating. As a result, indemnity payments are higher than the premiums collected. Given the difficulties that these problems present, there have been a number of studies that examined the existence and magnitude of moral hazard and adverse selection in crop insurance (i.e., See Smith and Goodwin, 1996; Knight and Coble, 1997; Roberts, Key, and O'Donoghue, 2006 for moral hazard studies; and, 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 adverse selection studies).

Even in light of the numerous moral hazard and adverse selection studies in crop insurance, there has been no study (to the best of our knowledge) that theoretically and empirically examined moral hazard and adverse selection in the context of a cost-of-

production (COP) crop insurance product. Most of the studies mentioned above are in the context of individual yield- or revenue-based crop insurance products (i.e., the ones that are predominantly offered in the United States (US) crop insurance program). A focus on COP insurance is especially important for the Philippines since the dominant, nationally-supported crop insurance offered in this country (for many years) is the COP type of crop insurance. But note that this particular COP crop insurance product is also slowly gaining traction in other countries as well. For example, a COP crop insurance product has recently been offered by private insurance companies in the US and Canada.[1] Thus, insights from a study that examines moral hazard and adverse selection for COP insurance in the Philippines may also provide important implications for a number of other countries that are offering this type of insurance (or thinking about offering it in the future).

Therefore, the objective of this article is to theoretically and empirically examine the moral hazard and adverse selection effects of COP crop insurance products. The defining feature of a COP crop insurance contract is that the indemnity payments are based on the costs of certain inputs (e.g. fertilizers and pesticides), but not others (e.g. effort). Farmers are required to submit a proposed farming plan and budget to the insurer at the time of insurance application and then they will be monitored by technicians from the insurer during the production season to make sure the actual amounts of inputs used are the same as the ones stated in the plan. The stated costs of these contracted inputs are then used to determine the indemnity payments should a loss occur. To the best of our knowledge, moral hazard and adverse selection behavior of farmers with such COP insurance coverage has not been theoretically and empirically assessed in the past, and as such this study also contributes to the literature in this regard.

In theoretically exploring the moral hazard and adverse selection effects of COP insurance, we build on the model developed by Horowitz and Lichtenberg (1993) (hereinafter called HL) by extending it: (1) to apply to a COP insurance product (rather than a revenue-based product as in HL), and (2) to include two input types (i.e., contracted and non-

[1] See the "Production Cost Insurance" products offered by ARMTech in the US and GlobalAgRisk Solutions in Canada: (1) ARMTech: https://armt.com/UploadFolder/file/2016ProductBrochures/pci%20for%20producers.pdf; and (2) GlobalAgRisk Solutions: https://agrisksolutions.ca/about#the-product.

contracted) rather than just one (the non-contracted) input type. We show that it is possible for both types of inputs to increase or decrease as one utilizes the COP insurance. This is somewhat different from the more traditional notion of moral hazard where one expects a reduction in input use with crop insurance coverage.[2] In addition, we explain how different beliefs about yields and potential causes of loss result in adverse selection outcomes in a COP insurance context.

As our theoretical analysis does not yield any clear predictions, we turn to empirical analysis to determine the signs of the moral hazard and adverse selection effects. Empirically, the main challenge is to separately estimate the moral hazard and adverse selection effects of COP crop insurance. The problem is that the same empirically observable phenomena is seen under both moral hazard and adverse selection. That is, under both moral hazard and adverse selection, we observe insured farmers being more likely to experience a loss (i.e., a positive relationship between insurance use and risk of loss is observed in both cases). Only under certain circumstances have the two effects been effectively disentangled from each other, especially in the case where one only has cross-sectional data on insurance participation and relevant outcome variables.[3] One example is Liu, Nestic and Vukina (2012), who use data from the Croatian health insurance market to separately estimate the adverse selection effect by comparing health expenditures by those who voluntarily bought supplemental insurance and those who were given supplemental insurance for free. The moral hazard effect was then estimated by comparing individuals who got the free supplemental insurance and those who had no insurance.

In this study, we utilize a survey question that elicits farmers' true preference for COP insurance coverage, which in turn allows us to separately estimate the moral hazard and adverse selection effects of COP crop insurance using a propensity score matching (PSM) approach akin to Liu, Nestic and Vukina (2012). Our empirical results suggest that farmers

[2] The non-contracted inputs here are akin to the "unobserved effort" in traditional one-dimensional moral hazard models where it is difficult for insurers to objectively measure the effort/input levels of the insured and offer insurance contracts based on these inputs. The expectation in this case is that this type of inputs (or effort) will decrease as one is covered by insurance.

[3] Note that there have also been several studies in the insurance economics literature that used detailed panel data sets and observed dynamic behavior to separately identify the adverse selection and moral hazard effects of insurance. See, for example, Abbring et al. (2003a, 2003b), Chiappori et al. (2006), and Dionne et al. (2013) for auto insurance applications, and Roberts et al., (2006) for a crop insurance application. Unfortunately, as explained below, we did not have access to a long, detailed panel data set to be able to use these types of approaches.

insured under a COP insurance contract spend more on chemical fertilizers and pesticides (i.e., the contracted inputs whose costs determine the indemnity payments), as compared to non-insured farmers. However, these same COP insured farmers are likely to use less of the non-contracted inputs. Since yield depends on both types of inputs, the final moral hazard effect of COP insurance on yields is ambiguous. For adverse selection, we find that famers who spend less on chemical fertilizers and pesticides tend to adversely select into a specific COP insurance contract that only covers losses from weather-related "natural disasters" (e.g., typhoon, drought, etc.). This suggests that these farmers may have private information on pest densities and/or soil conditions, such that they do not expect non-weather related losses from pests. As such, they adversely select into the "natural-disaster-only" COP insurance coverage.

The rest of the paper is organized as follows. The next section provides background on the Philippine 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 in the sixth section and the final section concludes.

**Empirical Setting: COP Crop Insurance in the Philippines**

Continued growth of 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 in rural areas. However, high poverty rates are still prevalent in many agricultural subsectors in the rural regions of the Philippines (Reyes et al., 2015). Three out of every four poor individuals in the Philippines come from agricultural households (Reyes et al., 2015a).

According to the Rural Poverty Report (2011) of the International Fund for Agricultural Development (IFAD), adverse weather shocks is the major factor that contributes to impoverishment in the Philippine agricultural sector. Farmers could mitigate the impact of adverse weather shocks in several ways. They can adopt on-farm strategies to alleviate production risks (i.e., crop diversification), or purchase crop insurance. The latter has been

recognized by the Philippine government as a viable institutional tool that can address negative shocks in agricultural production.

Crop insurance has been viewed as especially suitable in recent years when farmers have been confronted with new challenges imposed by climate change (e.g., particularly in light of recent "super-typhoon" Haiyan that devastated the central region of the Philippines in 2013). The Philippines has a tropical maritime climate and it is more prone to natural disasters, such as floods and typhoons. As such, this country is particularly vulnerable to the impacts of climate change. One adverse weather event can instantly cause severe losses and poor smallholder 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., 2015b).

*The PCIC COP Insurance Program for Corn*

Corn is one of the two major crops in the Philippines being insured by PCIC (the other one being rice).[4] In particular, there are two types of corn insurance offered by PCIC: (1) the natural-disasters-only type, and (2) the multi-risk type. The natural-disasters-only type

[4] The PCIC has seven major insurance product lines: rice, corn, high-value commercial crops (i.e., vegetables and fruits), livestock, fishery, non-crop agricultural assets, and term insurance packages.

insures farmers against crop loss caused only by natural (typically "weather-related") disasters, such as typhoons, floods, droughts and other natural calamities (i.e., earthquakes). The multi-risk type, on the other hand, covers a more comprehensive set of risks that includes all disasters covered under the natural-disaster-only program, plus losses from pest infestation and/or 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 them. The self-financed client, however, does not have loans from formal sources and only purchases crop insurance from PCIC.[5]

The insurance coverage (i.e., the liability amount) for corn is primarily determined based on the total cost of some production inputs, as indicated in the Farm Plan and Budget that the farmers are required to submit upon application. Insured farmers are then monitored by technicians during the production season to ensure the actual amounts of inputs used are the same as the ones stated in the Farm Plan and Budget. When a loss occurs, the costs of these inputs (e.g. fertilizers and pesticides) are then used to determine the indemnity payments. This makes the PCIC corn coverage a COP type of insurance and inputs such as fertilizers and pesticides the contracted inputs.

Reyes et al. (2015) point out that premium rates for corn insurance in the Philippines are largely based on historical data on damage rates (i.e., the ratio of indemnity to liabilities, which is also called the loss cost ratio) at the provincial level. Premium rates for the corn insurance product vary depending on: geographical location (i.e., different rates for different provinces), the type of insurance cover (natural-disaster-only 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

[5] 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.

weather events. Wet season cropping is also associated with higher premium rates (relative to the dry season cropping) because the 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., 2015b, 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' total (unsubsidized) premiums, on the other hand, are only shared with the government. But note that the total (unsubsidized) premium rate is typically the same for both the borrowing and the self-financed farmers.[6] 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-only 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 farmers 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% of the expected yield would make the insured farmers eligible for indemnity

[6] 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/.

payments. The insurance policy pays out indemnity in proportion to the percentage of loss due to specific insurable causes (as specified by the adjuster). For example, if the realized yield is just 70% of the expected yield for a farmer who insures the input cost or cost of production (i.e., the minimum coverage required by the PCIC), then the indemnity payments will be equal to 30% of the input costs. In this case, the farmer's net income would be the total revenues from selling 70% of expected yield less 70% of the input costs (i.e., since 30% of input costs is paid back as indemnity).

In 2012, 29% of the insured farmers had indemnities paid from the PCIC corn COP insurance program. As for the causes of loss, typhoons, floods and droughts were the main causes. For example, in 2012, an indemnity of PHP(Philippine Peso)15.77 (or US$0.374) million was paid for losses due to typhoons or floods, while PHP4.53 (or US$0.107) million and PHP6 (or US$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 develop a theoretical model to illustrate the moral hazard and adverse selection effects of insurance in the context of the Philippine crop insurance market. Our model builds on the work of HL, with the important difference that in their model, the indemnity payment for a qualified loss is a percentage of the expected revenue (e.g., a revenue-based insurance product), while in the Philippine crop insurance market that we model here, the indemnity payment is a percentage of the costs for a set of inputs.

Formally, assume a representative farmer owns one hectare of arable land.[7] The farmer's production technology can be described by the production function $Q(x, y, \omega)$, where $x$ is the set of inputs whose costs are used to determine the indemnity payments in the COP insurance contract (such as fertilizer and pesticides) and $y$ is the input whose cost is not a

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

determinant of the indemnity payments (such as effort). We define $\omega$ as a random variable affecting corn yield. It is assumed here that $\omega$ follows the distribution $g(\cdot)$ with support $[\omega_{min}, \omega_{max}]$. For example, when there are no natural disasters or crop diseases during the growing season, $\omega$ will be close to $\omega_{max}$. When damaging natural disasters and/or crop diseases occur, $\omega$ will be close to $\omega_{min}$. If less severe natural disasters and/or crop diseases occur, then $\omega$ will be somewhere in between $\omega_{min}$ and $\omega_{max}$. We further assume the following: $Q_x(x, y, \omega) > 0, Q_y(x, y, \omega) > 0$ and $Q_\omega(x, y, \omega) > 0$,[8] that is, the production function is increasing in all the inputs as well as the random shock.

The model has two stages. In the first stage, the farmer decides which type of COP insurance to purchase. The options include no insurance, the natural-disasters-only insurance and the multi-risk insurance. The insurance is such that if there is a qualifying loss and the loss is larger than 10% of the expected yield, then the indemnity payment will cover part of the farmer's total expenditures on input $x$, proportional to the loss in the expected yield. In the second stage, conditional on purchasing the COP insurance, the farmer needs to submit a Farm Plan and Budget, stating how much $x$ he plans to use and he will be monitored throughout the production process so that the stated $x$ amount is met. The farmer also chooses how much $y$ to use in this stage. At the end of the second stage, the realized yield is $Q(x, y, \omega)$. If the realized yield is less than $0.9\bar{Q}$ and the losses are covered by the insurance the farmer purchased in the first stage, then the insurance company will pay the farmer $\left(1 - \frac{Q(x,y,\omega)}{\bar{Q}}\right)\alpha x$. Here, $\alpha$ is the unit price of $x$ and $\bar{Q}$ is the expected yield, which, as in HL, is assumed to be determined exogenously by the insurance company based on historical farmer yields. The expression $\left(1 - \frac{Q(x,y,\omega)}{\bar{Q}}\right)$ is then the share of expected yield that is lost during production. Therefore, with the assumption $Q_\omega(x, y, \omega) > 0$, and given $x$ and $y$, there exists a trigger state $\omega^* = \omega(x, y, \bar{Q})$ such that for $\omega < \omega^*$, $Q(x, y, \omega) < 0.9\bar{Q}$ and the farmer will receive an indemnity payment.

[8] We also discuss below how our results will change when $Q_x(x, y, \omega) < 0$ and $Q_y(x, y, \omega) < 0$. But the assumption $Q_\omega(x, y, \omega) > 0$ is always maintained.

The model is solved using backward induction. We first examine the farmer's decisions in the second stage. Farmer *f*'s expected utility in this stage can be described by the following equation,

$$(1)\qquad EU(x,y) = \int_{\omega^*}^{\omega_{max}} u(pQ(x,y,\omega) - ax - by)g_f(\omega)d\omega + \int_{\omega_{min}}^{\omega^*} u\left(pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right)P_c g_f(\omega)d\omega + \int_{\omega_{min}}^{\omega^*} u(pQ(x,y,\omega) - ax - by)(1-P_c)g_f(\omega)d\omega$$

where $U$ is a utility function that exhibits risk aversion ($U' > 0, U'' < 0$), $b$ is the unit cost for $y$, $p$ is the output price and $P_c$ is the probability that the losses are covered by the insurance farmer $f$ purchased in the first stage. If the farmer chose not to purchase crop insurance in the first stage, $P_c = 0$. And the $P_c$ for the multi-risk insurance is larger than that of the natural-disasters-only insurance. The first order condition with respect to $x$ can be written as,

$$(2)\qquad \int_{\omega^*}^{\omega_{max}} u'\,[pQ(x,y,\omega) - ax - by][pQ_x(x,y,\omega) - a]g_f(\omega)d\omega - u[pQ(x,y,\omega^*) - ax - by]g_f(\omega^*)\frac{d\omega^*}{dx} + u\left[pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by\right]P_c g_f(\omega^*)\frac{d\omega^*}{dx} + \int_{\omega_{min}}^{\omega^*} u'\left[pQ(x,y,\omega) - \frac{Q_x(x,y,\omega)}{\bar{Q}}ax - by\right]\left[pQ_x(x,y,\omega) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - \frac{Q(x,y,\omega^*)}{\bar{Q}}a\right]P_c g_f(\omega)d\omega + u[pQ(x,y,\omega^*) - ax - by][1-P_c]g_f(\omega^*)\frac{d\omega^*}{dx} + \int_{\omega_{min}}^{\omega^*} u'\,[pQ(x,y,\omega) - ax - by][p(Q_x(x,y,\omega) - a][1-P_c]g_f(\omega)d\omega = 0,$$

and the first order condition with respect to $y$ is,

$$(3)\qquad \int_{\omega^*}^{\omega_{max}} u'[pQ(x,y,\omega) - ax - by]\left[pQ_y(x,y,\omega) - b\right]g_f(\omega)d\omega - u[pQ(x,y,\omega^*) - ax - by]g_f(\omega^*)\frac{d\omega^*}{dy} + u\left[pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by\right]P_c g_f(\omega^*)\frac{d\omega^*}{dy} + \int_{\omega_{min}}^{\omega^*} u'\left[pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right]$$

$$\left[pQ_y(x,y,\omega) - \frac{Q_y(x,y,\omega)}{\bar{Q}}ax - b\right]P_c g_f(\omega)d\omega +$$

$$u[pQ(x,y,\omega^*) - ax - by][1 - P_c]g_f(\omega^*)\frac{d\omega^*}{dy} +$$

$$\int_{\omega_{min}}^{\omega^*} u'[pQ(x,y,\omega) - ax - by]\left[pQ_y(x,y,\omega) - b\right][1 - P_c]g_f(\omega) = 0.$$

Denote the left hand side of equation (2) by $A$. The effect of insurance coverage on input $x$ can be derived by totally differentiating (2) with respect to $x$ and $P_c$ and then rearranging terms to get,

(4) $$\frac{dx}{dP_c} = -\frac{\frac{dA}{dP_c}}{\frac{dA}{dx}},$$

where $\frac{dA}{dx} < 0$ is the second order sufficient condition for $x$, defined implicitly in (2) to be the optimal solution to the maximization problem (1). As a result, $\frac{dx}{dP_c}$ has the same sign as $\frac{dA}{dP_c}$, which can then be derived from (2) as the following,

(5) $$\frac{dA}{dP_c} = \left\{[u(pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by) - u(pQ(x,y,\omega^*) - ax - by)]\, g_f(\omega^*)\frac{d\omega^*}{dx}\right\} +$$

$$\left\{\int_{\omega_{min}}^{\omega^*}[u'\left[pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right]\left[pQ_x(x,y,\omega) - \frac{Q_x(x,y,\omega)}{\bar{Q}}ax - \frac{Q(x,y,\omega)}{\bar{Q}}a\right] - u'[pQ(x,y,\omega) - ax - by][pQ_x(x,y,\omega) - a]]g_f(\omega)d\omega\right\}.$$

The first term in (5) (i.e., in the first pair of large curly brackets) is negative and the second term (i.e., in the second pair of large curly brackets) can be either positive or negative.[9] As a result, the effect of insurance coverage on the contracted input $x$ (the input whose cost determines the indemnity payments), $\frac{dx}{dP_c}$, can actually be either positive or negative.

Based on (4) and (5), COP crop insurance coverage influence the use of contracted input *x* through a couple of channels. First, COP insurance increases farmer's total income when the state of nature is below $\omega^*$. However, as the insured increases the use of $x$, the trigger level $\omega^*$ also decreases. In this case, the farmer will lose the additional income from COP

[9] See the Appendix for proof. Both results hold even when the farmer is risk neutral, that is, $U'' = 0$.

insurance when the true state of nature is actually just below $\omega^*$. Therefore, the farmer has less incentives to use more $x$ in this case. This explains why the first term of (5) (i.e., in the first set of curly brackets) is negative.

Second, the latter term in (5) (i.e., in the second set of curly brackets) indicates two possible effects of COP insurance on the use of contracted input *x*: (a) when $\omega < \omega^*$ as the case for the second term in (5), COP insurance gives the insured farmer additional income (aside from the income selling whatever is left of *Q*), and this consequently decreases the marginal utility of income for the farmer, which then gives the farmer incentives to spend and use more $x$; (b) the marginal cost of using $x$ changes from $a$ to $\left[\frac{Q_x(x,y,\omega)}{\bar{Q}}x + \frac{Q(x,y,\omega)}{\bar{Q}}\right]a$, and whether this is an increase or decrease depends on if $\frac{Q_x(x,y,\omega)}{\bar{Q}}x + \frac{Q(x,y,\omega)}{\bar{Q}}$ is larger or smaller than 1. For $\omega < \omega^*$, we know $\frac{Q(x,y,\omega)}{\bar{Q}}$<0.9. But the magnitude of $\frac{Q_x(x,y,\omega)}{\bar{Q}}x$ depends on the level $x$. Therefore, the marginal cost of using contracted input *x* can either decrease or increase because of COP insurance, and this part of the COP insurance effect on contracted input *x* can either be positive or negative. As a result, the second term in (5) (i.e., in the second set of curly brackets) can be either positive or negative, and the sign of expression (4) can be positive or negative.

The main result from equations (4) and (5) above is similar to the main implication from HL in the sense that it is possible for crop insurance coverage to either have: (1) a negative effect on input use (i.e., the traditional notion of moral hazard in crop insurance) or (2) a positive effect on input use. However, in HL, the positive input use effect only occurs if the specific input being considered is yield reducing (i.e., $Q_x(x, y, \omega) < 0$) and/or the farmer is risk averse. In contrast, the last part of the proof for Claim 2 in the Appendix show that the positive effect of COP insurance on contracted input use (*x*) is still possible even when: (a) the input is yield increasing ($Q_x(x, y, \omega) > 0$), which we maintain here, and (b) when the insured farmer is risk-neutral. Intuitively, since input *x* is the input whose cost determines the indemnity payment an insured farmer can possibly get with a COP insurance coverage, this situation can provide additional incentives to use more *x* (rather than less) even if the insured is risk-neutral (which reduces the incentives to use more $x$).

To assess the effect of COP insurance on the non-contracted input *y* (the input whose cost does not determine the indemnity payments), a similar mathematical derivation as in equations (4) and (5) can be performed. Let the left-hand side of equation (3) be denoted by *B*. The effect of insurance coverage on input $y$ can then be derived by totally differentiating (3) with respect to $y$ and $P_c$ and then rearranging terms to get the following,

$$\frac{dy}{dP_c} = -\frac{\frac{dB}{dP_c}}{\frac{dB}{dy}}, \tag{6}$$

where $\frac{dB}{dy} < 0$ is the second order sufficient condition for $y$ defined implicitly in (2) to be the optimal solution to the maximization problem (1). As a result, $\frac{dy}{dP_c}$ has the same sign as $\frac{dB}{dP_c}$, which can be derived from (3) as the following,

$$\begin{aligned} \frac{dB}{dP_c} = \Big\{ & [u(pQ(x,y,\omega^*) - \tfrac{Q(x,y,\omega^*)}{\bar{Q}} ax - by) - \\ & u(pQ(x,y,\omega^*) - ax - by)] g_f(\omega^*) \tfrac{d\omega^*}{dx} \Big\} + \\ & \Big\{ \int_{\omega_{min}}^{\omega^*} [u' \left[ pQ(x,y,\omega) - \tfrac{Q(x,y,\omega)}{\bar{Q}} ax - by \right] \\ & \left[ pQ_y(x,y,\omega) - \tfrac{Q_y(x,y,\omega)}{\bar{Q}} ax - b \right] - \\ & u'[pQ(x,y,\omega) - ax - by]\left[pQ_y(x,y,\omega) - b\right]] g_f(\omega) d\omega \Big\}. \end{aligned} \tag{7}$$

Similar to the discussion of equation (5), the first term in equation (7) (i.e., in the first pair of large curly brackets) is negative and the second term (i.e., in the second pair of large curly brackets) can be either positive or negative.[10] As a result, the effect of COP insurance coverage on non-contracted input $y$, $\frac{dy}{dP_c}$, can also be either positive or negative.

COP crop insurance coverage also alters the use of *y* through two channels. First, consistent with the discussion of equation (5), COP insurance coverage increases farmer's total income when the state of nature is below $\omega^*$. However, as the insured increases the use of $y$, the trigger level $\omega^*$ also decreases. In this case, the farmer will lose the additional income from COP insurance when the true state of nature is actually just below $\omega^*$.

[10] See the Appendix for proof. When the farmer is risk neutral, that is, $U'' = 0$, both terms are negative.

Therefore, the farmer has less incentives to use more $y$ in this case and this explains why the first term of (7) (i.e., in the first set of curly brackets) is negative.

Second, the latter term in (7) (i.e., in the second set of curly brackets) also reveals the two possible ways that COP insurance can affect the use of the non-contracted input *y*: (a) when $\omega < \omega^*$ as the case for the second term in (5), COP insurance gives the insured farmer additional income (aside from the income from selling whatever is left of *Q*), and this consequently decreases the marginal utility of income for the farmer, which then gives the farmer incentives to spend and use more $y$; (b) although COP crop insurance does not affect the unit cost of non-contracted input $y$, the insurance coverage changes the unit cost of $x$ from $a$ to $\frac{Q(x,y,\omega)}{\bar{Q}}a$, which increases with $y$ as $Q_y(x,y,\omega) > 0$. This then gives the farmer less incentives to use more $y$. As a result, the second term in equation (7) (i.e., in the second set of curly brackets) can also be either positive or negative, and the sign of expression (4) can either be positive or negative. However, one important difference between the second term in (7) and the second term in (5) above is that the second term in (7) will be negative for sure and hence the effect of insurance on the use of input $y$ (equation (6)) will be negative for sure if the input is yield increasing, that is, $Q_y(x,y,\omega) > 0$ as we have assumed and the farmer is risk neutral.[11]

Therefore, the main result from (7) is the same as the ones from HL, which means that COP insurance can either have a negative (i.e., traditional one-dimensional moral hazard) or a positive effect on the non-contracted input use. Moreover, we require exactly the same conditions as HL to obtain the latter result – that is, only when the input is yield reducing, that is, $Q_y(x,y,\omega) < 0$ and/or the farmer is risk averse, could the effect of COP insurance be positive. As the cost of input $y$ does not determine the indemnity payment the insured farmer can possibly get from the insurer, the insurance does not provide as much incentives to increase the its use as it does for the contracted input $x$. As a result, the effect could only be positive if the input is yield reducing and/or the farmer is risk averse (both of which increase the incentives to use more $y$).

[11] See the last part of the proof for Claim 4 in the Appendix.

Given the results above, and since yield depends on both types of inputs (i.e. contracted and non-contracted ones), the final moral hazard effect of COP insurance on the outcome variable $Q$ is ambiguous and would depend on the relative magnitudes of the effects of changes in $x$ and $y$. In addition, the fact that our model does not yield a clear prediction on the direction of the effect of COP insurance on input use and yield further motivates the necessity of our empirical analysis below.

Recall that the discussion above primarily pertains to the second stage of the farmers' overall decision problem. Following the backward induction solution to the overall decision problem, we now go back to the first stage decision where the farmer chooses the type of COP insurance to purchase (e.g., the natural-disasters-only type or the multi-risk type). Each COP insurance type comes with a different premium $P_I^j$ and a different coverage level $P_c^j$, where $j$ denotes the insurance plan. If the farmer chooses not to purchase insurance, then $P_I^j = P_c^j = 0$. The expected utility the farmer obtains from choosing plan $j$ is $EU^j(x_j^*, y_j^*)$, where the function $EU$ is defined in (1) and $x_j^*$ and $y_j^*$ are the optimal input decisions under plan $j$. The farmer will choose the plan that gives him the largest expected utility.

There are two potential sources of adverse selection in our model. First, the distribution of $\omega$ perceived by the insurance company when setting the expected yield $\bar{Q}$, $g_I(\cdot)$, can be different from that of farmer *f*, $g_f(\cdot)$. As a result, those farmers who expect a lower yield than $\bar{Q}$ adversely select themselves into purchasing crop insurance. Second, different farmers can have different beliefs (i.e., and private information that leads to these beliefs). As a result, some farmers self-select into the natural-disasters-only COP insurance while others self-select into the multi-risk COP insurance. Different farmers self-select (or adversely select) into different insurance plans depending on their beliefs about the distribution of the losses $g_f(\omega)$.

Given the theoretical discussion above, farmers who have private information that makes them believe that they are likely to suffer from both weather-related (e.g., floods, droughts) and/or non-weather-related (e.g., pests and diseases) losses, would purchase the multi-risk COP insurance type. On the other hand, producers having private information that leads them to believe that they are more likely to only suffer from weather-related losses (rather than

pests and diseases) will only purchase the natural-disasters-only COP insurance. The latter behavior (and beliefs) is consistent with producers that do not expect to use as much chemical fertilizer and pesticides in the first place (i.e., they expect to apply less since they have private information about the lower likelihood of being affected by pests and diseases). Thus, we hypothesize that producers that expect to spend lower than average amounts of chemical fertilizer and pesticides likely have private information about soil conditions and pest/disease incidence such that these producers will adversely select into the natural-disaster-only COP insurance.

**Data Description**

As our model predicts an ambiguous relationship between COP insurance coverage and input use and yield, an empirical analysis is warranted to further investigate the effects of COP insurance. To do so, we use a survey dataset from the Philippines. The data set 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 a 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 the PCIC corn insurance program. The data on the area devoted to corn and the number of insured producers were obtained from the Philippine 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 non-open pollinated seeds (i.e., hybrid or genetically modified seeds). Second, 20 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 kilograms per hectare, six farmers with historical mean yields larger than 12,000kg per hectare and 18 farmers with missing historical yields were dropped from this sample. Finally, 10 farmers with missing information on the type of insurance purchased were dropped. As a result, there are 370 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 by lenders. We divide farmers into three groups based on their responses to these two questions. Among insured farmers, those in the VOLUNTARY group stated that they voluntarily chose to purchase insurance, and would have purchased it even if it was not required by lenders. Farmers in the FORCED group are those who were "forced" to purchase insurance due to lender requirements, and would have not done so if it was not required. Farmers in the third group, the NO group, had the option to purchase insurance but willingly 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 COP crop insurance in the Philippines. Specifically, we can write a farmer's outcome variable $Y_i$ (i.e., which can be measures of input use or corn yields, in our context) 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 $\varepsilon_i$ with mean zero:

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

*Identification*

From (8), it is clear that the average outcome difference between the FORCED group and NO group is the following,

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

If conditional on observables, the average farmer unobserved heterogeneity is the same for the FORCED group and the NO group (i.e., 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 $\alpha$. If the following condition holds $E(a_i|X, FORCED) > E(a_i|X, NO)$, which means on average the unobserved heterogeneity in the FORCED group is larger than that of the NO group, 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 the FORCED and NO groups are the same in the sense that both types do not have real demand for crop insurance. But they may differ since farmers in group FORCED are required to purchase crop insurance by their creditors and they need a loan for their operation in that particular crop year. This implies that farmers in the NO group may have a more favorable financial status than farmers in the FORCED group. Some reasons for farmers in the FORCED group to have a worse financial situation (compared those in the NO group) is either they have an inherently low wealth status or that they had a bad harvest in one of the previous years. In our matching estimation approach (described further below), we control for farmer's wealth and previous farming 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 (8) also implies that the average outcome difference between group VOLUNTARY and group FORCED is:

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

The true adverse selection effect is the difference in average farmer unobserved heterogeneity

between farmers who have real demand for crop insurance (those in the VOLUNTARY group) and those who do not have real demand for crop insurance (those in the FORCED and NO groups). That is, $\gamma = E(a_i|X, VOLUNTARY) - E(a_i|X, FORCED \text{ and } NO)$. Under the same assumption above, that is, $E(a_i|X, FORCED) = E(a_i|X, NO)$, we have $E(a_i|X, FORCED) = E(a_i|X, FORCED \text{ and } NO)$. 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 $\gamma$. But again, if the $E(a_i|X, FORCED) = E(a_i|X, NO)$ assumption does not hold, then the adverse selection effect would be either underestimated or overestimated.

*Matching Estimation*

The empirical estimation of the moral hazard and adverse selection effects of COP crop insurance is carried out based on equations (9) and (10) through 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 effect into the natural-disaster-only insurance, and the adverse selection effect into the multi-risk insurance.

Under the assumption $E(a_i|X, FORCED) = E(a_i|X, NO)$, equation (9) implies that a consistent estimator for the average moral hazard effect (i.e., based on behavior of farmers in FORCED and NO groups) is:

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

where $N_1$ is the number of farmers in the 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,

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

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,

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

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 that $E(a_i|X, FORCED) = E(a_i|X, NO)$, expression (10) implies that a consistent estimator for the average adverse selection effect is:

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

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 VOLUNTARY group can be estimated using,

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

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

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

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

*Outcome and Control Variables*

In our analysis, we focus on two outcome ($Y$) variables: farmer $i$'s yield ($Yield_i$) and his total expenditure on chemical fertilizers and pesticides ($Expenditure_i$). Many studies in the

literature focus on these two variables separately when studying moral hazard and adverse selection effects in the context of crop insurance (see Smith and Goodwin (1996) on fertilizer/pesticide use, and Quiggin, Karagiannis, Stanton (1993) on production/yield). Also, as discussed above, we need to control for a set of observed farm/farmer characteristics $X_i$ in the matching estimations. These variables are determinants of the outcome variables and controlling for them makes our 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. In addition, lagged yield is a key determinant of the current yield because farming conditions have some persistence across years.

A cognitive ability variable is also included as a control variable. This variable was collected using a word recall approach (similar to the one used in Fang, Keane, and Silverman (2008)). Each respondent was asked to repeat a list of ten words after listening to those words spoken by the enumerator. The first recall exercise was conducted at the beginning of the interview and a second recall exercise was conducted at the end of the interview. The total number of words (out of 20) that 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 of farm decisions and outcomes, including yield and input use. Older farmers are more experienced in farming and are typically more confident in coping with farm risks, which can in turn influence yield and input use decisoons. This is why age ($Age_i$) is included as a control variable. Household size ($Hs_i$) is another variable inclued in the specification. Families with babies and older parents may not be as productive as those with a smaller household. Also, families with several children need to pay for these kids' educational expenses, and may spend less on farm 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 topographical features of the farmer's field(s) partly determine the impact of weather variables (i.e., risk of flooding for low-lying areas is higher, realtive to those in more elevated areas) , and hence may influence yield outcomes and input use decisions, respectively. For this reason, we control for topography using a dummy variable $Flat_i$, which equals 1 if farmer $i$ reported that his or her land is plain/flat, and equals 0 if it is mountainous/hilly.

Yield and input decisions also depend on the type of seeds (or crop variety) used by the producer. The $Hybrid_i$ variable is equal to 1 if farmer $i$ uses non-genetically modified (GM) hybrid seeds and 0 if GM seeds are used. Newly developed GM seeds offer various new features, such as inherent resistance to pests such Asian corn borers (e.g., Bt corn), so less pesticides need to be used, and herbicide tolerance (e.g., Round-up Ready corn), so that farmers can apply weedicides without damaging the plant.

The total farm area is denoted as $Area_i$. It is expected that farmers with larger farm ares (and fields) tend to be wealthier and this variable is included to capture the effects of wealth levels on input use and yields. This variable also captures the effect of scale on the outcome variables of interest. Two variables are used to control for farm 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/or raises livestock tells us how diversified the farm is. A farmer that only produces corn might be more productive due to specialization. On the other hand, farmers who also raise livestock can apply livestock manure to their fields instead of using chemical fertilizers. Diversification also allows use to control for the level of risk management (since diversfication is also considered an income smoothing mechanism). The variable $DistanceRoad_i$ is also included in the specification and it is the distance between farmer $i$'s main field and the nearest road. Better road access allows farmers to take better care of their fields (e.g. applying pesticides more frequently) and gives them better access to input markets. As a result, yields are likely to be higher if the farmers has better road acess.

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 (i.e., 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 and other effects that vary at the regional level (including premiums). All the variables discussed in this section, together with their definitions, are listed in Table 1. The summary statistics for these variables are reported in Table 2 by group and insurance type.

## Results and Discussion

### *PSM Estimation Results*

The first step in PSM is to estimate the propensity scores. To do so, we estimate a Logit regression model for each matching estimation and the propensity score for a farmer is the predicted probability for him/her being in the treated group (i.e., FORCED in the moral hazard case and VOLUNTARY in the adverse selection case). The Logit estimation results for all four matching scenarios are presented in Table 3. The densities of the computed propensity scores by matching scenario and group are shown in Figures 1 and 2.

The estimated average moral hazard and adverse selection effects based on the PSM procedure (i.e., see equations (11) and (14)), are presented in Table 4. First, COP crop insurance coverage, either the natural-disaster-only or the multi-risk type, have a positive, statistically significant effect on total chemical fertilizer and pesticide expenditures. Note that fertilizer and pesticides are the contracted inputs. Our theoretical analysis above shows that, unlike in a traditional one-input moral hazard model, it is possible for the COP insurance to have a positive effect on the use of the contracted inputs and our empirical finding here confirms this possibility.

Farmers that were "forced" to purchase natural-disaster-only coverage spent 1,580 Philippine Pesos (PhP) per hectare more on chemical fertilizers and pesticides, as compared to farmers that did not willingly buy crop insurance. On the other hand, farmers that were "forced" to buy the multi-risk insurance coverage had PhP 2,050 per hectare more expenditure on chemical fertilizers and pesticides, relative to farmers that did not willingly buy crop insurance. Both results are statistically significant (at the 5% level).

This finding implies that basing indemnity payments on contracted input use (through a COP insurance product) can lead farmers to make more investments on these inputs (e.g., chemical fertilizers and pesticides, in our case). Following the discussion of equation (5), the empirical result above suggests that the marginal benefits from increased COP coverage (through higher application of the contracted inputs) and, the consequent increased likelihood of payments in case of a loss, overcomes the marginal costs of additional contracted input use.

The positive contracted input use effect of COP insurance also suggest that linking indeminity payemnts to the costs of certain inputs can indeed mitigate the traditional moral hazard effect of insurance on input use. Based on the empirical results here, there is no evidence of moral hazard for COP insurance coverage on the contracted inputs such as fertilizer and pesticides in the Philippines. In addition, the result that multi-risk insurance coverage has a larger positive effect on chemical fertilizer and pesticide expenditures (relative to those with the natural-disaster-only coverage) implies that more comprehensive protection from risks provided by COP coverage gives more incentives to apply these contracted inputs.

From Table 4, we also find that farmers who were "forced" to purchase the natural-disaster-only COP insurance have yields that are 927 kg per hectare lower than those farmers who voluntarily chose not to purchase insurance coverage, and this effect is statistically significant at the 1% level. However, we did not find any statistically significant difference between farmers that were "forced" to get the multi-risk COP crop insurance and those who voluntarily did not get COP insurance coverage.

This finding provides evidence that COP crop insurance coverage in the Philippines may still result in the traditional moral hazard effect. Note that yield is a function of both

contracted (i.e., like the aforementioned chemical fertilizer & pesticides), and unobservable, non-contracted inputs (i.e., unobserved effort). Thus, the negative COP insurance effect on yields provide an indication that COP insured producers still reduce unobservable effort (i.e., the standard one-dimensional moral hazard story) and this exerts downward pressure on yield outcomes. Our theoretical analysis above predicts that it is possible for farmers with COP coverage to reduce non-contracted input use and our empriical finding here confirms this possibility.

For the case of the natural-disaster-only COP insurance, the negative effect of COP insurance on unobserved effort may have ovewhelmed the positive effect of COP insurance on contracted inputs, such that the net yield outcome is negative (i.e., yields of FORCED is statistically lower than those NO). On the other hand, given the stronger positive effect of multi-risk COP coverage , the positive effect of COP insurance on contracted inputs is now more likely to be larger than the negative effect on unobserved effort. Therefore, the combined COP insurance effect on unobserved effort and contracted input use may have resulted in the non-significance of the COP on yield otucomes in Table 4 (i.e., the moral hazard PSM estimate on the yield outcome is insignficant for multi-risk COP insurance). Empirically, the moral hazard effect of COP insurance on yield outcomes is more strongly felt for natural-disaster only insurance and not so much for multi-risk insurance.

Turning to adverse selection, our results in Table 4 show that producers in the VOLUNTARY group who willingly bought natural-disaster-only coverage tend to have statistically lower chemical fertilizer & pesticide expenditures (i.e., by PhP 1,200) relative to those in the FORCED group with natural-disaster-only coverage (at the 1% level of significance). However, the statistically lower expenditures was not observed for the the multi-risk insurance case.

These adverse selection results suggest that farmers who tend to use less chemicals self-select (or adversely select) into the natural-disaster-only COP insurance. In contrast, there is no such evidence for adverse selection into the multi-risk COP insurance.This finding implies that some farmers may possess private knowledge regarding whether their fields will suffer from losses due to pests and other plant diseases (i.e, losses from non-natural disasters). Those farmers who believe their fields are not likely to suffer from such risks generally spend

less on chemical fertilizer & pesticides, and consequently adversely select into purchasing natural-disaster-only COP insurance. Therefore, these results are consistent with our hypothesiss regarding the adverse selection effect of COP insurance in the theoretical framework.

*Robustness Checks*

One important assumption underlying the PSM estimation above is the overlapping condition, which means that, for any farmer in one group, we can find another farmer in the other group that has a very similar propensity score. Figures 1 and 2 plots the densities of the estimated propensity scores for all the farmers in our dataset by group and matching estimation considered. For the two estimations of the moral hazard effects of COP insurance (Figure 1A and 2A), 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 very close propensity score. This implies that the overlapping condition holds better for farmers in the NO group. Therefore, in our robustness check here, we repeat the same PSM procedure conducted above but only for farmers in the NO group and the results are reported in Table 5. The results are very similar to our main results in Table 4, both in terms of the signs and magnitudes of the moral hazard effects as well as their statistical significance.

Similarly, Figure 1B and 2B shows that the overlapping condition is more likely to hold for farmers in the FORCED group in the matching estimation to analyze the adverse selection effects of COP insurance. That is, for each farmer in the FORCED group, we can easily find farmers in the VOLUNTARY group with similar propensity scores. But for each farmer in the VOLUNTARY group (especially those with high propensity scores), we cannot easily find farmers in the FORCED group with similar propensity scores. We therefore repeat the estimation of the adverse selection effects for farmers matched to the FORCED group only and also report results in Table 5. Again, our adverse selection results are very similar to our main results in Table 4.

## Conclusions and Implications

In this study, we theoretically and empirically investigate the moral hazard and adverse selection effects of COP insurance products. One of the main features of this coverage is that indemnity payments are linked to the total cost of some inputs used but not others.

Our results suggest that this kind of COP insurance coverage results in increased application of the contracted inputs (rather than a reduction in application, as is predicted in traditional theories of one-dimensional moral hazard). Since COP insurance coverage is primarily based on how much of the contracted input is used, there are incentives in this kind of insurance design to apply more of these contracted inputs (especially when there is strong beliefs about the likelihood of losses). However, the traditional moral hazard result still follows for non-contracted inputs (i.e., like unobserved effort) in this type of COP insurance product. Given that yield depends on both types of inputs (i.e. contracted and non-contracted ones), the final moral hazard effect of COP insurance on yields is ambiguous.

For adverse selection, our results indicate that famers who intend to spend less on chemical fertilizers and pesticidesare are likely to adversely select into a specific COP insurance contract that only covers losses from weather-related "natural disasters" (e.g., typhoon, drought, etc.). This suggests that these farmers may have private information on pest densities and/or soil conditions, such that they do not expect non-weather related losses. As such, they adversely select into the "natural-disaster-only" COP insurance coverage.

Overall, our analysis imply that a COP insurance design can provide economic incentives for curbing moral hazard behavior only for the contracted input, but unobservable inputs to production would still be subject to moral hazard. Therefore, it is important to highlight here that contracting itself do not "solve" all moral hazard problems for COP insurance coverage. In addition, although not explicitly considered in the present analysis, an important policy consideration when offering COP crop insurance is the cost of verifying the actual use of the contracted inputs (which needs to be weighed against the reduction in overall moral hazard from this effort). For insurance companies, the benefits and costs of verifying the used of contracted inputs for all insured producers should be compared to the benefits and costs of alternative approaches to curbing moral hazard; say, random input verification of a subset of producers.

The adverse selection result from this study also point to important implications for improving the COP insurance offering available in the Philippines. Since we find some evidence that producers who tend to use less chemical inputs are the ones who often adversely-select into the natural-disaster-only type, it may be prudent to somehow incorporate the level of chemical use in the premium-rating procedure for COP insurance. As mentioned above, premium rates (for a particular insurance type and season) only varies depending on the risk type of a province. Therefore, our adverse selection results imply that the Philippine insurance program should consider including chemical input use level as a "risk" indicator when rating the COP insurance product. Moreover, these resuls imply that other historical risk indicators, like average historical yields, should also be considered in order to enhance and fine tune the premium rating procedures for COP insurance in the Philippines (i.e., so that premiums are more carefully tailored to the risks of individual producers and adverse seelction is potentially reduced).

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Table 1. List and Definition of Variables used in the Empirical Analysis

| Variable | Unit | Definition |
|---|---|---|
| Dependent/Outcome variables: | | |
| *Yield* | '000 kg/hectare | Yield of the largest parcel per hectare in 2012 |
| *Expenditure* | 10,000 PHP | Total expenditure on chemical fertilizer and pesticide inputs (that is monitored by technicians) |
| Independent/Control variables: | | |
| *HistoricalYield* | '000 kg/hectare | Mean yield per hectare for 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 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 |
| *Isabela* | | 1=Isabela and 0 otherwise |
| *Pangasinan* | | 1=Pangasinan and 0 otherwise |

Table 2. Summary Statistics (by Insurance Coverage Choice and Type of Farmer)

| Variable | Natural-Disaster-Only Insurance | | | | Multi-Risk Insurance | | | | No Insurance | |
|---|---|---|---|---|---|---|---|---|---|---|
| | FORCED Group | | VOLUNTARY Group | | FORCED Group | | VOLUNTARY Group | | | |
| | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. | Mean | St. Dev. |
| *Yield* | 6.15 | 3.35 | 6.04 | 2.46 | 4.46 | 2.76 | 6.38 | 3.06 | 5.52 | 2.73 |
| *Expenditure* | 1.19 | 0.38 | 1.13 | 0.28 | 1.29 | 0.32 | 1.30 | 0.37 | 1.13 | 0.37 |
| *HistoricalYield* | 5.43 | 2.53 | 4.78 | 2.14 | 4.72 | 1.81 | 5.92 | 2.43 | 4.68 | 2.08 |
| *Cognitive* | 7.21 | 3.31 | 5.87 | 3.37 | 9.38 | 3.36 | 8.27 | 4.13 | 6.92 | 3.12 |
| *Sex* | 0.71 | 0.46 | 0.82 | 0.39 | 0.59 | 0.50 | 0.61 | 0.49 | 0.73 | 0.45 |
| *Age* | 43.17 | 10.96 | 48.76 | 12.26 | 46.52 | 9.42 | 46.09 | 10.50 | 49.15 | 12.18 |
| *Hs* | 4.69 | 1.48 | 4.74 | 1.50 | 4.84 | 1.58 | 4.39 | 1.65 | 4.58 | 1.74 |
| *Education* | 8.85 | 3.31 | 8.45 | 3.55 | 8.78 | 3.40 | 9.89 | 3.43 | 8.20 | 2.94 |
| *Flat* | 0.91 | 0.28 | 0.97 | 0.17 | 0.92 | 0.27 | 0.98 | 0.15 | 0.92 | 0.27 |
| *Hybrid* | 0.60 | 0.49 | 0.76 | 0.43 | 0.75 | 0.44 | 0.80 | 0.41 | 0.70 | 0.46 |
| *DistanceRoad* | 1.35 | 2.35 | 0.95 | 1.33 | 1.36 | 3.11 | 0.91 | 1.32 | 0.82 | 1.29 |
| *Area* | 2.08 | 1.83 | 2.17 | 1.64 | 2.95 | 3.44 | 3.11 | 1.84 | 2.37 | 2.33 |
| *OtherCrop* | 0.44 | 0.50 | 0.50 | 0.51 | 0.53 | 0.50 | 0.68 | 0.47 | 0.52 | 0.50 |
| *Livestock* | 0.17 | 0.38 | 0.16 | 0.37 | 0.25 | 0.44 | 0.14 | 0.35 | 0.13 | 0.34 |
| *RiskAverse* | 0.19 | 0.39 | 0.08 | 0.27 | 0.11 | 0.31 | 0.25 | 0.44 | 0.22 | 0.42 |
| *Isabela* | 0.58 | 0.50 | 0.55 | 0.50 | 0.11 | 0.31 | 0.09 | 0.29 | 0.37 | 0.48 |
| *Pangasinan* | 0.21 | 0.41 | 0.34 | 0.48 | 0.22 | 0.42 | 0.61 | 0.49 | 0.30 | 0.46 |
| No. of Obs. (Total N=370) | 48 | | 38 | | 55 | | 44 | | 185 | |

Table 3. Parameter Estimates from the First Stage Logit Regression (used to estimate propensity scores for the PSM Approach).

| Variable | Natural-disaster-only Crop Insurance | | | | Multi-Risk Crop Insurance | | | |
|---|---|---|---|---|---|---|---|---|
| | Moral Hazard[1] [*FORCED-NO*] | | Adverse Selection[2] [*VOLUNTARY-FORCED*] | | Moral Hazard[3] [*FORCED-NO*] | | Adverse Selection[4] [*VOLUNTARY-FORCED*] | |
| | Coeff. | St. Err. | Coeff. | St. Err. | Coeff. | St. Err. | Coeff. | St. Err. |
| *HistoricalYield* | 0.26*** | 0.11 | -0.25 | 0.17 | 0.004 | 0.10 | 0.12 | 0.14 |
| *Cognitive* | -0.03 | 0.08 | -0.27 | 0.18 | 0.18** | 0.08 | -0.08 | 0.08 |
| *Sex* | -0.51 | 0.46 | 3.46*** | 1.28 | -1.30 | 0.43 | -0.03 | 0.55 |
| *Age* | -0.03* | 0.02 | 0.10** | 0.05 | 0.003 | 0.02 | -0.04 | 0.03 |
| *Hs* | 0.11 | 0.13 | 0.48 | 0.34 | -0.05 | 0.12 | -0.05 | 0.18 |
| *Education* | 0.07 | 0.08 | 0.30 | 0.19 | 0.12* | 0.07 | 0.02 | 0.09 |
| *Flat* | -0.39 | 0.84 | 2.35 | 1.71 | 0.47 | 0.83 | 1.68 | 1.43 |
| *Hybrid* | 0.22 | 0.48 | 0.32 | 0.87 | 0.21 | 0.46 | 0.39 | 0.70 |
| *DistanceRoad* | 0.20* | 0.11 | -0.65** | 0.28 | 0.07 | 0.10 | 0.01 | 0.12 |
| *Area* | -0.01 | 0.10 | 0.42* | 0.26 | -0.04 | 0.07 | 0.01 | 0.10 |
| *OtherCrop* | 0.86* | 0.53 | -2.34** | 1.08 | -0.53 | 0.44 | 0.14 | 0.69 |
| *Livestock* | 0.01 | 0.57 | -0.22 | 1.13 | 0.95** | 0.50 | -0.13 | 0.69 |
| *RiskAverse* | -0.18 | 0.55 | -3.35** | 1.66 | -1.27** | 0.58 | 0.61 | 0.72 |
| *Isabella* | 0.67 | 0.62 | 0.49 | 1.22 | -2.52*** | 0.70 | 0.68 | 1.01 |
| *Pangasinan* | -0.73 | 0.71 | 1.14 | 1.28 | -0.42 | 0.62 | 1.27* | 0.76 |
| Constant | -2.62 | 2.02 | -10.81** | 5.72 | -2.60 | 1.72 | -0.96 | 2.71 |
| Psuedo-$R^2$ | 0.13 | | 0.35 | | 0.24 | | 0.17 | |
| No. of Obs. | 210 | | 62 | | 227 | | 91 | |

Notes: [1] Dependent variable (= 1) for the *FORCED* group who bought natural-disaster-only; [2] Dependent variable (= 1) for the *VOLUNTARY* group who bought natural-disaster-only; [3] Dependent variable (= 1) for the *FORCED* group who bought multi-risk insurance, [4] Dependent variable (= 1) for the *VOLUNTARY* group who bought multi-risk insurance; and; (5) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table 4. PSM Estimation Results: Moral Hazard and Adverse Selection Effects (by Insurance Type) Over the Full Sample

| Insurance/ Outcome Variable | Moral Hazard Effect [*FORCED-NO*] | | | Adverse Selection Effect [*VOLUNTARY-FORCED*] | | |
|---|---|---|---|---|---|---|
| | Coeff. | St. Err. | P-value | Coeff. | St. Err. | P-value |
| A. Natural-Disaster-Only | | | | | | |
| *Expenditure* | 0.158** | 0.08 | 0.04 | -0.120*** | 0.05 | <0.01 |
| *Yield* | -0.927*** | 0.30 | <0.01 | 0.167 | 0.67 | 0.80 |
| No. of Obs. | | 210 | | | 62 | |
| B. Multi-risk | | | | | | |
| *Expenditure* | 0.205*** | 0.05 | <0.01 | -0.011 | 0.11 | 0.92 |
| *Yield* | 0.286 | 0.51 | 0.57 | -0.454 | 0.29 | 0.11 |
| No. of Obs. | | 227 | | | 91 | |

Notes: (1) The Moral Hazard Effects above was calculated using Eq. 11. (2) The Adverse Selection Effects above was calculated using Eq. 14. (3) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Table 5. PSM Estimation Results: Moral Hazard and Adverse Selection Effects (by Insurance Type) Over Selected Groups

| Insurance/ Outcome Variable | Moral Hazard Effect Averaged over the NO Group [*FORCED-NO*] | | | Adverse Selection Effect Averaged over the FORCED Group [*VOLUNTARY-FORCED*] | | |
|---|---|---|---|---|---|---|
| | Coeff. | St. Err. | P-value | Coeff. | St. Err. | P-value |
| A. Natural-Disaster-Only | | | | | | |
| *Expenditure* | 0.188** | 0.10 | 0.07 | -0.184** | 0.09 | 0.04 |
| *Yield* | -1.123*** | 0.37 | <0.01 | 0.789 | 0.50 | 0.12 |
| No. of Obs. | | 210 | | | 62 | |
| B. Multi-risk | | | | | | |
| *Expenditure* | 0.194*** | 0.06 | <0.01 | -0.116 | 0.10 | 0.26 |
| *Yield* | 0.617 | 0.69 | 0.37 | -0.332 | 0.33 | 0.31 |
| No. of Obs. | | 227 | | | 91 | |

Notes: (1) The Moral Hazard Effects above was calculated using Eq. 13. (2) The Adverse Selection Effects above was calculated using Eq. 16. (3) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Figure 1. Densities of Propensity Scores for Natural-Disaster-Only Insurance Effects

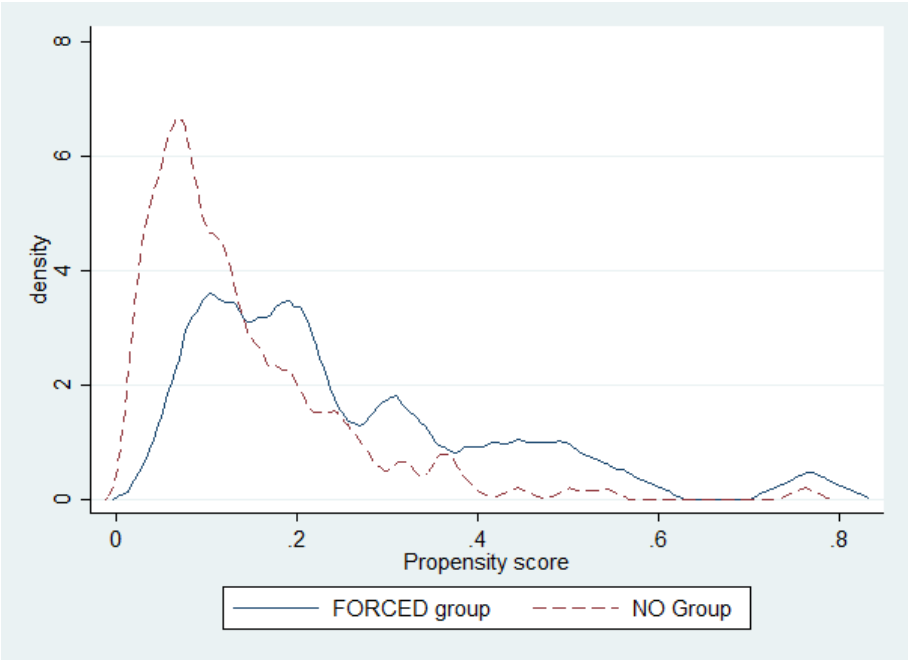


Figure 1A. Moral Hazard Under Natural-Disaster-Only Insurance

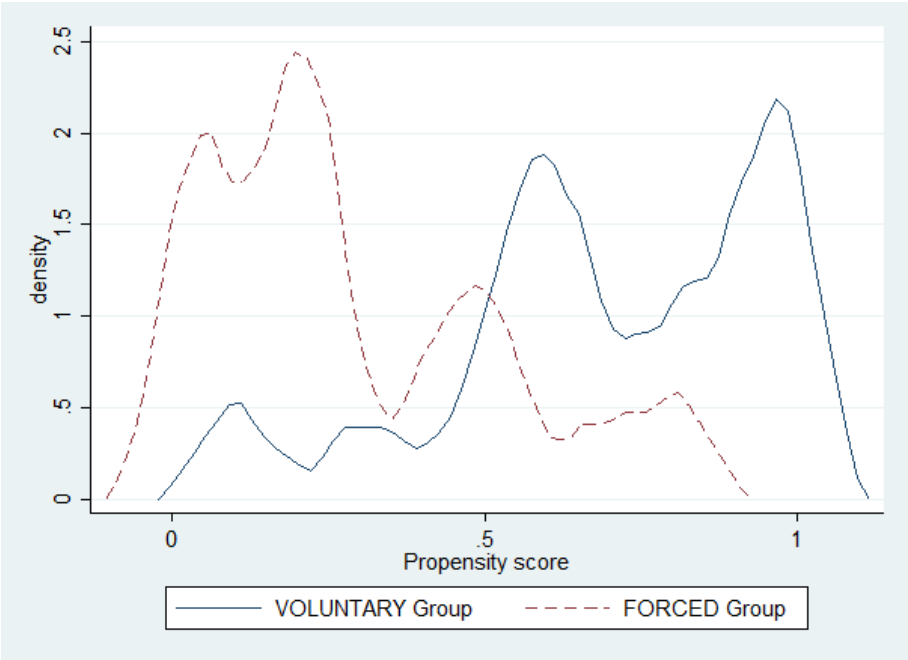


Figure 1B. Adverse Selection Under Basic Cover

Figure 2. Densities of Propensity Scores for Multi-Risk Insurance Effects

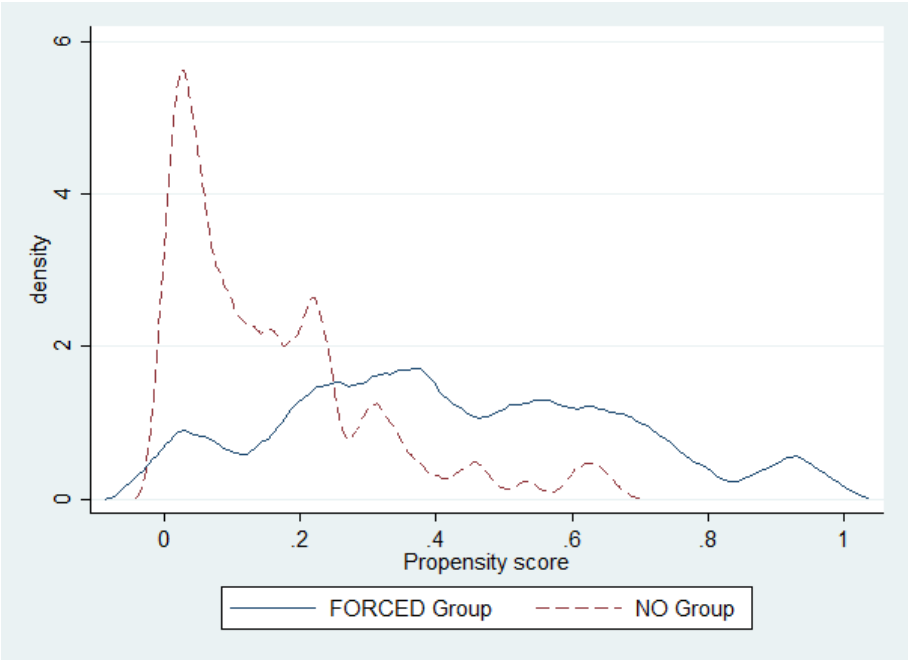


Figure 2A. Moral Hazard Under Multi-Risk Cover

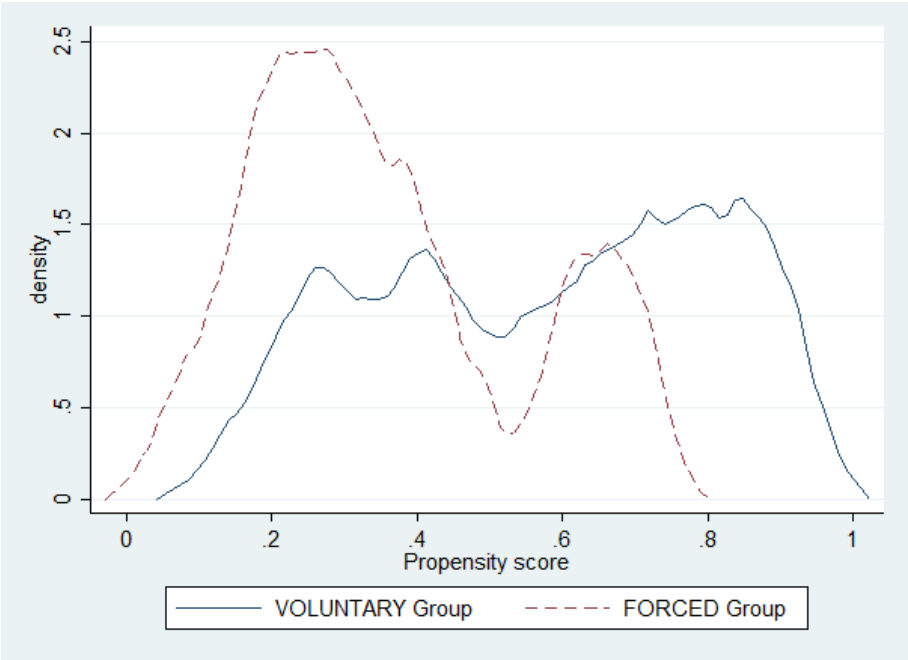


Figure 2B. Moral Hazard Under Multi-Risk Cover

## APPENDIX

**Claim 1: The first term of (5) is negative.**

**Proof:** First, by definition, $Q(x,y,\omega^*) = 0.9\bar{Q}$. Therefore, $pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by > pQ(x,y,\omega^*) - ax - by$ and hence $u\left(pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by\right) > u(pQ(x,y,\omega^*) - ax - by)$. Second, totally differentiating $Q(x,y,\omega^*) = 0.9\bar{Q}$ with respect to $x$ and $\omega^*$ and rearranging terms gives $\frac{d\omega^*}{dx} = -\frac{Q_x(x,y,\omega^*)}{Q_w(x,y,\omega^*)}$, which is negative as we assume $Q_x(x,y,\omega^*) > 0$ and $Q_w(x,y,\omega^*) > 0$. As a result, the first term of (5) is negative. This completes the proof.

**Claim 2: The second term of (5) can be either positive or negative.**

**Proof:** The second term of (5) can be written as $\int_{\omega_{min}}^{\omega^*}[C(\omega)D(\omega) - E(\omega)F(\omega)]g_f(\omega)d\omega$, where $C(\omega) = u'\left[pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right]$, $D(\omega) = pQ_x(x,y,\omega) - \frac{Q_x(x,y,\omega)}{\bar{Q}}ax - \frac{Q(x,y,\omega)}{\bar{Q}}a$, $E(\omega) = u'[pQ(x,y,\omega) - ax - by]$ and $F(\omega) = pQ_x(x,y,\omega) - a$. Therefore, the second term of (5) is a weighted sum of $C(\omega)D(\omega) - E(\omega)F(\omega)$ with $\omega \in [\omega_{min}, \omega^*]$ and weights $g_f(\omega)$. Below we discuss the sign of $C(\omega)D(\omega) - E(\omega)F(\omega)$ for a representative $\omega$ and show it can be either positive or negative. Then, $\int_{\omega_{min}}^{\omega^*}[C(\omega)D(\omega) - E(\omega)F(\omega)]g_f(\omega)d\omega$ can either be positive or negative, depending on the specification of $g_f(\cdot)$. This is because as long as $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive for some values of $w$ and negative for other values, then the weighted sum can be either positive or negative, depending on the weights assigned todifferent values of $w$.

We now show for a representative $w$, $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative. First, note that by defnition, for $\omega \in [\omega_{min}, \omega^*]$, $\frac{Q(x,y,\omega)}{\bar{Q}} < 0.9$. As a result, $0 < C(\omega) = u'\left(pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right) < u'(pQ(x,y,\omega) - ax - by) = E(\omega)$ because $U' > 0, U'' < 0$. Then, depending on the relationships among $D(\omega)$, $F(\omega)$ and 0, we have the following six cases.

Case 1: $F(\omega) < D(\omega) < 0$, then $C(\omega)D(\omega) > E(\omega)D(\omega)$. So, $C(\omega)D(\omega) - E(\omega)F(\omega) > E(\omega)D(\omega) - E(\omega)F(\omega) = E(\omega)\big(D(\omega) - F(\omega)\big) > 0$. So in this case, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive.

Case 2: $F(\omega) < 0 < D(\omega)$, then $C(\omega)F(\omega) > E(\omega)F(\omega)$. So, $C(\omega)D(\omega) - E(\omega)F(\omega) > C(\omega)F(\omega) - E(\omega)F(\omega) = F(\omega)\big(C(\omega) - E(\omega)\big) > 0$. So in this case, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive.

Case 3: $0 < F(\omega) < D(\omega)$, then $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative.

Case 4: $D(w) < F(w) < 0$, then $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative.

Case 5: $D(\omega) < 0 < F(\omega)$, then $C(\omega)F(\omega) < E(\omega)F(\omega)$ so $-C(\omega)F(\omega) > -E(\omega)F(\omega)$. As a result, $C(\omega)D(\omega) - E(\omega)F(\omega) < C(\omega)D(\omega) - C(\omega)F(\omega) = C(\omega)\big(D(\omega) - F(\omega)\big) < 0$. So in this case, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is negative.

Case 6: $0 < D(\omega) < F(\omega)$, then $C(\omega)D(\omega) < E(\omega)D(\omega)$ so $C(\omega)D(\omega) - E(\omega)F(\omega) < E(\omega)D(\omega) - E(\omega)F(\omega) = E(\omega)\big(D(\omega) - F(\omega)\big) < 0$. So in this case, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is negative.

These six cases show clearly that for a representative $\omega$, $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative. Also, note that even when the farmer is risk neutral, that is, $U'' = 0$, this result still holds. In this situation, for any $w$, $C(\omega) = E(\omega)$. In case 3, $C(\omega)D(\omega) - E(\omega)F(\omega)$ becomes positive and in case 4, $C(\omega)D(\omega) - E(\omega)F(\omega)$ becomes negative. Results for other cases remain the same. This completes the proof.

**Claim 3: The first term of (7) is negative.**

**Proof:** First, by definition, $Q(x,y,\omega^*) = 0.9\bar{Q}$. Therefore, $pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by > pQ(x,y,\omega^*) - ax - by$ and hence $u\left(pQ(x,y,\omega^*) - \frac{Q(x,y,\omega^*)}{\bar{Q}}ax - by\right) > u(pQ(x,y,\omega^*) - ax - by)$. Second, totally differentiating $Q(x,y,\omega^*) = 0.9\bar{Q}$ with respect to $y$ and $\omega^*$ and rearranging terms gives $\frac{d\omega^*}{dy} = -\frac{Q_y(x,y,\omega^*)}{Q_w(x,y,\omega^*)}$, which is negative as we assume $Q_y(x,y,\omega^*) > 0$ and $Q_w(x,y,\omega^*) > 0$. As a result, the first term of (7) is negative. This completes the proof.

**Claim 4: The second term of (7) can be either positive or negative.**

**Proof:** The second term of (7) can be written as $\int_{\omega_{min}}^{\omega^*}[C(\omega)G(\omega) - E(\omega)H(\omega)]g_f(\omega)d\omega$, where $G(\omega) = pQ_y(x,y,\omega) - \frac{Q_y(x,y,\omega)}{\bar{Q}}ax - b$ and $H(\omega) = pQ_y(x,y,\omega) - b$. Therefore, the second term of (7) is a weighted sum of $C(\omega)G(\omega) - E(\omega)H(\omega)$ with $\omega \in [\omega_{min}, \omega^*]$ and weights $g_f(\omega)$. Below we discuss the sign of $C(\omega)G(\omega) - E(\omega)H(\omega)$ for a representative $w$ and show it can be either positive or negative. Then, $\int_{\omega_{min}}^{\omega^*}[C(\omega)G(\omega) - E(\omega)H(\omega)]g_f(\omega)d\omega$ can either be positive or negative, depedning on the specification of $g_f(\cdot)$. This is because as long as $C(\omega)G(\omega) - E(\omega)H(\omega)$ is positive for some values of $w$ and negative for other values, then the weighted sum can be either positive or negative, depending on the weights assigned todifferent values of $w$.

We now show for a representative $w$, $C(\omega)G(\omega) - E(\omega)H(\omega)$ can be either positive or negative. First, note that by defnition, for $\omega \in [\omega_{min}, \omega^*]$, $\frac{Q(x,y,\omega)}{\bar{Q}} < 0.9$. As a result, $0 < C(\omega) = u'\left(pQ(x,y,\omega) - \frac{Q(x,y,\omega)}{\bar{Q}}ax - by\right) < u'(pQ(x,y,\omega) - ax - by) = E(\omega)$ because $U' > 0, U'' < 0$. Second, note that $\frac{Q_y(x,y,\omega)}{\bar{Q}}ax > 0$ as we assume $Q_y(x,y,\omega) > 0$, so $G(w) = pQ_y(x,y,\omega) - \frac{Q_y(x,y,\omega)}{\bar{Q}}ax - b < pQ_y(x,y,\omega) - b = H(w)$. Then, depending on the relationships among $G(\omega)$, $H(\omega)$ and 0, we have the following three cases.

Case 1: $G(\omega) < H(\omega) < 0$, then $C(\omega)G(\omega) - E(\omega)H(\omega)$ can either be positive or negative.

Case 2: $G(\omega) < 0 < H(\omega)$, then $C(\omega)H(\omega) < E(\omega)H(\omega)$ so $-C(\omega)H(\omega) > -E(\omega)H(\omega)$. As a result, $C(\omega)G(\omega) - E(\omega)H(\omega) < C(\omega)G(\omega) - C(\omega)H(\omega) = C(w)\big(G(w) - H(w)\big) < 0$. Therefore, in this case, $C(\omega)G(\omega) - E(\omega)H(\omega)$ is negative.

Case 3: $0 < G(\omega) < H(\omega)$, then $C(\omega)G(\omega) < E(\omega)G(\omega)$ so $C(\omega)G(\omega) - E(\omega)H(\omega) < E(\omega)G(\omega) - E(\omega)H(\omega) = E(\omega)\big(G(\omega) - H(\omega)\big) < 0$. Therefore, in this case, $C(\omega)G(\omega) - E(\omega)H(\omega)$ is negative.

These three cases show clearly that for a representative $\omega$, $C(\omega)G(\omega) - E(\omega)H(\omega)$ can be either positive or negative and hence the second term of (7) can be either positive or negative. Furthermore, when the farmer is risk neutral, that is, $U'' = 0$, for any $w$, $C(\omega) = E(\omega)$. With this, in case 1, $C(\omega)G(\omega) - E(\omega)H(\omega)$ becomes negative. Results for other cases remain the same. Therefore, for a representative $\omega$, $C(\omega)G(\omega) - E(\omega)H(\omega)$ is negative and hence the second term of (7) is negative for sure when the farmer is risk neutral.