Input Use under Cost-of-Production Crop Insurance: Theory and Evidence

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ABSTRACT

There have been a number of previous studies that examined the effects of yield- or revenue-based crop insurance products on input use of farmers. However, no study has specifically investigated the input use impacts of a cost-of-production (COP) crop insurance policy, even though this type of crop insurance is the predominant one used in several other countries outside of the U.S. (such as the Philippines and China). This article aims to theoretically and empirically examine the effect of a COP crop insurance product on farmers' chemical input use. Our theoretical model suggests that the effect of COP insurance on input use can either be positive or negative, with the resulting impact depending on the strengths of: (a) the traditional moral hazard effect of insurance (i.e., an input use decreasing effect); versus (b) the marginal incentives to apply more inputs due to input levels being the main determinant for expected indemnity amounts in this type of insurance (i.e., an input use increasing effect). A survey data set from corn farmers in the Philippines is then used to empirically illustrate how a particular COP insurance product influences input use in a real-life context. In this case, we find that COP insurance increases the use of chemical inputs (e.g., fertilizers and weedicides), implying that the positive marginal incentive to apply more inputs dominates the negative moral hazard effect.

Keywords: Cost-of-Production Crop Insurance; Moral Hazard

JEL Classifications: Q18; Q12; G22

1. Introduction

Since crop insurance programs are perceived to have less trade-distorting effects by the World Trade Organization (WTO), a number of developed and developing countries have steadily replaced direct government payments with crop insurance as the primary means to stabilize farm incomes. Over the last two decades, increasingly higher premium subsidies have been used to encourage farmers to purchase crop insurance. In the Philippines, for example, approximately 5.96B Philippine Pesos (PhP) (or ~US$ 111M) worth of agricultural products are covered with crop insurance in 2010 (Yorobe and Luis, 2015). The growth in crop insurance uptake worldwide has made it one of the most important risk management tools that farmers across the globe utilize. However, over the years, there has been policy interest with respect to the input use effect of crop insurance since its use has been shown to influence fertilizer and chemical application, which in turn could affect run-off to and pollution of nearby bodies of water. Due to this environmental concern, there have been several academic studies that examined the effect of particular types of insurance (i.e., mostly yield and revenue based policies) on farmer input use.

One such study is the seminal work of Horowitz and Lichtenberg (1993) (hereinafter called HL) who proposed a model of crop insurance with the key prediction that the effect of crop insurance on input use can either be positive or negative. Two incentives drive their result. First, with crop insurance, a risk averse farmer's expected income is higher, which in turn leads to a lower marginal utility of income for the farmer. As a result, the farmer spends more on inputs and the effect is larger if the farmer is more risk averse. The second effect is the traditional moral hazard effect. With crop insurance, the input has no effect on revenue in a larger set of states of nature and hence the farmer has fewer incentives to spend on inputs. Using data collected from a survey in 1987, their empirical analysis showed crop insurance had a positive effect on input use for corn producers in their sample. In a related study, Wu (1999) found that the intensive-margin effect of crop insurance on chemical use was negative (based on data from corn farmers in the Central Nebraska basin of the US), but the extensive-margin effect of crop insurance on chemical use was positive.

In contrast, using data from corn farmers in Iowa, Babcock and Hennessy (1996) showed that insured farmers in their sample used less chemical inputs than non-insured farmers. Smith and Goodwin (1996) and Goodwin, Vandeveer, and Deal (2004) reported similar empirical findings using different datasets from the U.S. Moreover, there are also studies that found crop insurance having little effect on input use. Quiggin, Karagiannis and Stanton (1993) found a negative but insignificant effect of insurance on input use. Goodwin and Smith (2003) showed that the Federal crop insurance program had little impact on soil erosion, implying that the insurance effect on input use may be negligible. A recent study by Weber, Key and O'Donoghue (2016) also found that insurance had little direct effect on input use.

One important feature to note in this previous literature is that all of the studies cited above investigated the input use effect of a specific set of crop insurance products – individual yield- or revenue-based crop insurance. These crop insurance products are the ones that are predominantly offered and used by farmers in the US Federal crop insurance program. Therefore, these past studies may offer limited lessons and policy insights for other countries where the individual cost-of-production (COP) type of crop insurance plays a more prominent role, such as in China and the Philippines. For example, China's COP insurance program only compensates farmers a portion of the costs spent on inputs if yields fall below insured levels (Zhong and Zhu, 2017). Likewise, in the Philippines, farmers are required to submit an input use plan upon COP insurance application, and the indemnity payment is a percentage of the total input costs stated in the plan (Reyes et al., 2015; He et al., 2018). The COP insurance products are structured differently as compared to the yield- and revenue-based products in the US and may hence affect input use differently.

In addition, the use of COP insurance programs have been growing rapidly in China and the Philippines. China's crop insurance premium income increased from \$3.54 billion in 2012 to \$6.14 billion in 2016, and in the Philippines, the number of insured farmers increased from 0.148 million in 2009 to 1.195 million in 2015. This expansion in the uptake of COP insurance programs signals that there is a need for further research on the possible consequences of COP insurance programs on input use (and ultimately its effect on the environment). Note that COP crop insurance is also slowly gaining markets in more developed 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 COP insurance may also provide implications for a number of other countries that have started offering or thinking about offering this type of insurance in the future.

[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

In this study, we offer the first theoretical analysis, as well as an empirical illustration, of the possible effects of COP crop insurance on farmer input use. Our theoretical model builds on the work of HL, with the important difference that we specifically model a COP insurance product while HL considered a yield-based insurance policy. Similar to HL, our model predicts that the effect of COP insurance on input use can either be positive or negative, but the underlying drivers and conditions for these effects to occur are different. In particular, the positive input use effect in HL only occurs if the specific input being considered is yield reducing and/or the farmer is risk averse. In contrast, we find that the positive effect of COP insurance on input use is still possible even when the input is yield increasing and the insured farmer is risk-neutral. Intuitively, given that input costs partly determines the magnitude of indemnity payments from COP coverage, a COP insured farmer has additional marginal incentives to use more inputs (i.e., the input use increasing effect). On the other hand, we also theoretically find that the traditional moral hazard effect of insurance (i.e., the input use decreasing effect) also plays a role in the eventual input levels utilized by COP insured farmers.

We empirically demonstrate the effect of COP insurance on fertilizer and chemical use based on a cross-sectional survey data set from corn farmers in the Philippines. As briefly mentioned above, the COP crop insurance contract offered in the Philippines determines the indemnity payments based on the cost of production inputs (e.g., fertilizers and pesticides). 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 sent by the insurer during the production season (i.e., to make sure the actual amounts of inputs applied are consistent with the ones stated in the plan). The stated costs of these contracted inputs are then used to calculate the indemnity payment if losses occur. Our empirical results show that COP insured Philippine corn farmers use more fertilizers and weedicides, as well as spend more on total chemical use, relative to non-COP-insured farmers. This suggests that the positive marginal incentives to apply more inputs, given the indemnity structure of the COP insurance, dominates the negative moral hazard effect in this empirical context, which may then have potentially negative consequences for the environment (in terms of chemical run-off in the soil and non-point source pollution).

The remainder of the paper is organized as follows. The next section introduces the Philippine crop insurance program. The third section presents the model and discusses its key implications. Our data is described in section four and section five details the estimation strategy. Empirical results are discussed in section six in and the final section concludes.

2. 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., 2015a). 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 a 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 "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.

2.1 The Philippine Crop Insurance Corporation (PCIC)

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

Unlike in some 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 also viewed as a mechanism that provides incentives for lending institutions to make loans available to producers, especially in underdeveloped rural areas where credit access may be an issue (Reyes et al., 2015b).

2.2 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).[2] 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 insures farmers against crop loss caused only by natural (i.e., typically "weather-related") disasters, such as typhoons, floods, droughts and 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.[3]

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

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[2] 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.

[3] 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., 2015a). 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.

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 are the contracted inputs.

Reyes et al. (2015b) 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 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. Note that the total (unsubsidized) premium rate is typically the same for both the borrowing and the self-financed farmers.[4] 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.

[4] 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/.

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) actually 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 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.

3. Theoretical Framework

In this section, we develop a theoretical model to illustrate the effect of COP insurance on input use in the context of the Philippine crop insurance market. Our model builds upon 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 (that is, they model a revenue-based insurance product), while in the Philippine crop insurance market that we model here, the indemnity payment is a percentage of the input costs.

Formally, assume a representative farmer owns one hectare of arable land.[5] The farmer's production technology can be described by the production function $Q(x, \omega)$, where x is a set of inputs whose costs are used to determine the indemnity payments in the COP insurance contract (such as fertilizer and pesticides). We define ω as a random variable affecting corn yield. It is assumed that ω follows the distribution of $g(\cdot)$ with support $[\omega_{min}, \omega_{max}]$. For example, when there are no natural disasters or crop diseases during the growing season, ω will be close to ω_{max}. When damaging natural disasters and/or crop diseases occur, ω will be close to ω_{min}. If less severe natural disasters and/or crop diseases occur, then ω will be in between ω_{min} and ω_{max}. We further assume $Q_x(x, \omega) > 0$, and $Q_\omega(x, \omega) > 0$,[6] that is, the production function is increasing in the inputs as well as the random shock.

Upon 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 has the choice of purchasing either the natural-disasters-only insurance or 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 x, proportional to the qualified loss in the expected yield. To be specific, at the end of the growing season, suppose the realized yield is $Q(x, \omega)$. If the realized yield is less than $0.9\bar{Q}$ and the losses are covered by the insurance type the farmer purchased, then the insurance company will pay the farmer $\left(1 - \frac{Q(x,\omega)}{\bar{Q}}\right) \alpha x$. Here, α is the unit price of x and $\bar{Q}$ is the expected yield, which, as in the HL model, is assumed to be determined exogenously by the insurance company based on historical farmer yields. The expression $\left(1 - \frac{Q(x,\omega)}{\bar{Q}}\right)$ is then the share of expected yield that is lost during production. Therefore, with the assumption $Q_\omega(x, \omega) > 0$, given x, there exists a trigger state $\omega^* =$

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

[6] We also discuss below how our results will change when $Q_x(x, \omega) < 0$. The assumption $Q_w(x, w) > 0$ is always maintained.

$\omega(x, \bar{Q})$ such that for $\omega < \omega^*$, $Q(x, \omega) < 0.9\bar{Q}$ and the farmer will receive an indemnity payment.

With these assumptions, farmer *f*'s expected utility can be described by the following equation,

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

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

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

Denote the left hand side of (2) as 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 rearrange terms to get,

$$(3) \qquad \frac{dx}{dP_c} = -\frac{\frac{dA}{dP_c}}{\frac{dA}{dx}},$$

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 be derived from (2) as the following,

(4) $$\frac{dA}{dP_c} = \left[u\left(pQ(x,\omega^*) - \frac{Q(x,\omega^*)}{\bar{Q}}ax\right) - u(pQ(x,\omega^*) - ax)\right] g(\omega^*)\frac{d\omega^*}{dx} + \int_{\omega_{min}}^{\omega^*}\left[u'\left(pQ(x,\omega) - \frac{Q(x,\omega)}{\bar{Q}}ax\right)\left(pQ_x(x,\omega) - \frac{Q_x(x,\omega)}{\bar{Q}}ax - \frac{Q(x,\omega)}{\bar{Q}}a\right) - u'(pQ(x,\omega) - ax)(pQ_x(x,\omega) - a)\right]g(\omega)d\omega$$

The first term in (4) is negative (Claim 1) and the second term can be either positive or negative (Claim 2).[7] As a result, the effect of insurance coverage on the contracted input x, $\frac{dx}{dP_c}$, can actually be either positive or negative.

Based on (3) and (4), COP crop insurance coverage influences the use of input x through a couple of channels. First, COP insurance increases farmer's total income when the state of nature is below ω^*. However, as the insured increases the use of x, the trigger level ω^* 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 ω^*. Therefore, the farmer has less incentives to use more x in this case. This explains why the first term of (4) (i.e., in the first set of square brackets) is negative.

Second, the latter term in (4) (i.e., in the second set of square 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 (4), 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 $\left[\frac{Q_x(x,\omega)}{\bar{Q}}x + \frac{Q(x,\omega)}{\bar{Q}}\right]a$, and whether this is an increase or decrease depends on whether $\frac{Q_x(x,\omega)}{\bar{Q}}x + \frac{Q(x,\omega)}{\bar{Q}}$ is larger or smaller than 1. For $\omega < \omega^*$, we know $\frac{Q(x,\omega)}{\bar{Q}}$<0.9. But the magnitude of $\frac{Q_x(x,\omega)}{\bar{Q}}x$ depends on the level of x. Therefore, the marginal cost of x can either decrease or increase because of the COP insurance, and this part of the COP insurance effect on x can either be positive or negative.

The main result from equations (3) and (4) 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

[7] See proofs of claim 1 and claim 2 in the Appendix. Both results hold even when the farmer is risk neutral, that is, $u'' = 0$.

input use. However, in HL, the positive input use effect only occurs if the specific input being considered is yield reducing (i.e., $Q_x(x, \omega) < 0$) and/or the farmer is risk averse. In contrast, the last part of the proof for Claim 2 in the Appendix shows that the positive effect of COP insurance on input (*x*) is still possible even when: (a) the input is yield increasing ($Q_x(x, \omega) > 0$), which we maintain here, and (b) when the insured farmer is risk-neutral. Intuitively, since input *x* is the input whose costs determine the indemnity payment with COP insurance coverage, the theoretical model above suggests that COP insurance can provide additional incentives to use more *x* even if the insured is risk-neutral. This is the key difference between the COP insurance and the individual yield- or revenue-based insurance in terms of its effect on input use.

3.1 Numerical Examples

The possible effects on input use of COP insurance are best illustrated using a couple of numerical examples. In the first set of examples, farmers are considered to be risk averse. For both examples in this setting, we assume the utility function takes the form of $U(w)=\frac{(w+10)^{1-\theta}}{1-\theta}$, where the original wealth of the farmer is assumed to be 10, w is the profit from agricultural production and the risk aversion parameter θ is set to be 0.8.[8] The production function is specified to be $Q(x, \omega) = \omega \frac{x}{1+x}$ and the output and input prices p and a are set to be 10 and 1, respectively. We can easily check that with this specification of the output function, we have $Q_x(x, \omega) > 0$. Finally, $\bar{Q}$ is chosen to be the expected output $E[Q(x^*, \omega)]$ (i.e., expectation over ω), when x^* is the amount of input used, and where x^* is the optimal amount of input use without the insurance.

In the first example, ω is assumed to follow the uniform distribution on [0, 1], representing the scenario where good, medium and bad yields are equally likely. In this case, the optimal input use without insurance can be calculated by maximizing the following objective function, $EUN(x) = \int_0^1 \frac{1}{(10\omega\frac{x}{1+x} - x + 10)^2} d\omega$, which gives $x^* = 1.1643$. As a result, $\bar{Q} = \int_0^1 \omega \frac{x^*}{1+x^*} d\omega = 0.5 \frac{x^*}{1+x^*} = 0.2690$ and the trigger level $\omega^*(x) = 0.9\bar{Q}/\frac{x}{x+1} = 0.2421\frac{x+1}{x}$. With these, we can then calculate the optimal input use with a full coverage COP ($P_c = 1$) by maximizing the following objective function

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[8] Shi, Chavas and Lauer (2013) used the same utility function.

(5) $$EU(x) = \int_{\omega^*}^{1} u\left(10\omega\frac{x}{1+x} - x\right) d\omega + \int_{0}^{\omega^*} u\left(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.2690}x\right) d\omega$$

$$= -0.5[\int_{\omega^*}^{1} \frac{1}{(10\omega\frac{x}{1+x} - x+10)^2} d\omega + \int_{0}^{\omega^*} \frac{1}{(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.2690}x+10)^2} d\omega].$$

The optimal input use in this case x^{cop} is 1.3641, which is larger than x^*, the optimal input use without the COP insurance. In this particular numerical example, the COP insurance incentivizes farmers to use more inputs (i.e., input-use increasing effect of COP).

In our second example, ω is assumed to follow the Beta (5,1) distribution, representing the scenario where the probability for a good outcome in yield is larger than that of a bad outcome. In this case, using exactly the same procedure described above, we can obtain the optimal input use without the COP insurance as $x^* = 1.8723$. As a result, $\bar{Q} = \int_0^1 \frac{x^*}{1+x^*} 5\omega^5 d\omega = 0.5432$. And the trigger level $\omega^*(x) = \frac{0.9\bar{Q}}{\frac{x}{x+1}} = 0.4888\frac{x+1}{x}$. With these, we can then calculate the optimal input use with a full coverage COP ($P_c = 1$) by maximizing the following objective function,

(6) $$EU(x) = \int_{\omega^*}^{1} u\left(10\omega\frac{x}{1+x} - x\right) 5\omega^4 d\omega + \int_{0}^{\omega^*} u\left(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.5432}x\right) 5\omega^4 d\omega$$

$$= -2.5[\int_{\omega^*}^{1} \frac{1}{(10\omega\frac{x}{1+x} - x+10)^2} \omega^4 d\omega + \int_{0}^{\omega^*} \frac{1}{(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.5432}x+10)^2} \omega^4 d\omega].$$

The optimal input use in this case x^{cop} is 1.8077, which is smaller than x^*, the optimal input use without the COP insurance. For this second numerical example, the COP insurance discourages farmers to use inputs (i.e., input-use decreasing effect of COP). The two simple numerical examples above show that the possible effect of COP insurance can either be positive or negative when farmers are risk averse.

Next, we present two more numerical examples assuming farmers are risk neutral. In this third case, we assume that the utility function takes the form of $U(w) = w+10$, and keep all other specifications and parameter values the same as above. For this third example, ω is again assumed to follow the uniform distribution on [0, 1]. In this case, the optimal input use without insurance can be calculated by maximizing the following objective function, $EUN(x) = 10\int_0^1 \omega\frac{x}{1+x} d\omega - x + 10$, which gives $x^* = 1.2361$. As a result, $\bar{Q} = \int_0^1 \omega\frac{x^*}{1+x^*} d\omega = 0.2764$

and the trigger level $\omega^*(x) = 0.9\bar{Q}/\frac{x}{x+1} = 0.2488\frac{x+1}{x}$. With these figures, we can then calculate the optimal input use with a full coverage COP ($P_c = 1$) by maximizing the following objective function

$$(7) \qquad EU(x) = \int_{\omega^*}^{1}\left(10\omega\frac{x}{1+x} - x\right)d\omega + \int_{0}^{\omega^*}\left(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.2764}x\right)d\omega.$$

The optimal input use in this case x^{cop} is 1.4068, which is larger than x^* (the optimal input use without the COP insurance). Thus, in this third specific numerical example, the COP insurance incentivizes farmers to use more inputs (i.e., input-use increasing effect of COP), even under risk neutrality.

For the fourth example (under risk neutral utility function), ω is again assumed to follow the Beta (5,1) distribution. In this case, the optimal input use without insurance can be calculated by maximizing the following objective function, $EUN(x) = \int_0^1(10\omega\frac{x}{1+x} - x + 10)5\omega^4 d\omega$, which gives $x^* = 1.8868$. As a result, $\bar{Q} = \int_0^1 \frac{x^*}{1+x^*}5\omega^5 d\omega = 0.5447$ and the trigger level $\omega^*(x) = \frac{0.9\bar{Q}}{\frac{x}{x+1}} = 0.4902\frac{x+1}{x}$. Using these figures, we can then calculate the optimal input use with a full coverage COP insurance ($P_c = 1$) by maximizing the following objective function,

$$(8) \qquad EU(x) = \int_{\omega^*}^{1}\left(10\omega\frac{x}{1+x} - x + 10\right)5\omega^4 d\omega + \int_{0}^{\omega^*}\left(10\omega\frac{x}{1+x} - \frac{\omega\frac{x}{1+x}}{0.5447}x + 10\right)5\omega^4 d\omega.$$

The optimal input use in this case x^{cop} is 1.8186, which is smaller than x^*, the optimal input use without the COP insurance. Therefore, in this fourth example, the COP insurance discourages farmers to use inputs (i.e., input-use decreasing effect of COP), even under risk neutrality. These two latter examples show that even in the case where farmers are risk neutral, the possible effect of COP insurance can also be either positive or negative.

3.2 The Case When $Q_x(x, \omega) < 0$

The theoretical analysis so far hinges upon the assumption that $Q_x(x, \omega) > 0$, that is, the input x is yield increasing. This is generally true for weedicides and pesticides as they are damage abating, but may not be true for fertilizers. Fertilizers might promote both crop and weed growth and as a result, the final effect on yield might be ambiguous. Also, under certain extreme weather conditions, fertilizers can be even yield reducing (Horowitz and Lichtenberg, 1994). Therefore, it is also worthwhile to reexamine our main results under the alternative assumption of $Q_x(x, \omega) < 0$.

In this case, it can be shown that the first term in (4) is positive (Claim 3 in Appendix) and the second term can still be either positive or negative (Claim 4 in Appendix).[9] As a result, the effect of insurance coverage on the contracted input x, $\frac{dx}{dP_c}$, can still be either positive or negative. Therefore, our main theoretical result above continues to hold even in the case of possibly yield reducing inputs.

4. Data

As our model predicts an ambiguous relationship between COP insurance coverage and input use, an empirical illustration is warranted to further investigate the effects of COP insurance in a particular real-life context. To do so, we use a survey dataset from the Philippines. The dataset 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 (see Figure 1). 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 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, 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, with half of them insured and the other half uninsured. The questionnaire elicits a wide range of farmers' information including the farmer's demographic background, socio-economic

[9] See proofs of claim 3 and claim 4 in the Appendix. Again, both results hold even when the farmer is risk neutral, that is, $u'' = 0$.

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, 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, twenty two "farmers" surveyed who were paid care-takers of the fields were dropped because these respondents 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 eighteen farmers with missing historical yields were dropped from this sample. As a result, there are 402 farmers in our working sample.

5. Empirical Strategy

We estimate the effect of insurance on input use, by estimating the following empirical model,

$$y_i = \beta_0 + \beta_1 Insurance_i + \beta_2 X_i + u_i, \quad (9)$$

where y_i is the amount of input used. We consider the amounts of fertilizers ($Fertilizer_i$), weedicides ($Weedicide_i$), and pesticides ($Pesticide_i$) used per hectare, as well as the total expenditure on these three inputs ($Expenditure_i$), as dependent variables in our empirical analysis. $Insurance_i$, in this case, is a 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 inputs used. Below we discuss the definition of each variable and the justifications for including them in the empirical specification.

Since each farmer has land with different qualities, faces different weather conditions, and uses different technology, we include the average value of the reported yields per hectare for the two most recent years, that is, 2010 and 2011 yields (i.e., the $HistoricalYield_i$ variable) in the specification. The intent is for this variable to control for the potential effect of unobserved individual heterogeneity on input use (which cannot be captured by province dummies). Input decisions also depend on 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 like Asian corn borer, which lead to less pesticides needing to be used for pest control. The presence of inherent herbicide tolerance in some GM crops also allow farmers to apply more weedicides without damaging their crops.

The variable $DistanceRoad_i$ is the distance between farmer i's field 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 (such as those included in the study), 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. The total farming area is denoted as $Area_i$. It is expected that larger farms are associated with more farming assets, so this variable is used to examine the wealth effect of insurance 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 farm diversification. $Livestock_i$ is set to 1 if the farmer raises any livestock and 0 otherwise. Farmers can apply livestock manure to their fields instead of fertilizers. $OtherCrop_i$ is set to 1 if the farmer plants other crops aside from corn and 0 otherwise. Farmers who grow other crops may face less risks due to diversification, and this risk reduction may in turn affect input choices.

A risk aversion measure ($RiskAverse_i$) is also included in the empirical specification because risk-averse farmers may use more conservative management approaches, such as using more chemicals to minimize uncertainty in their farming income. Farmers' risk preference is elicited in the survey using 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 the $RiskAverse_i$ variable is set to 1 for these farmers (zero otherwise). Finally, province dummies are included to control for heterogeneity in input prices or any other effects that vary at the regional level.[10]

[10] Village information is missing for some farmers so that village dummies cannot be used.

5.1 Identification

One challenge in estimating the reduced form equation in (5) 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 (IV) approach. For a variable to be a good instrument, it has to satisfy two conditions. First, it has to be excluded from (5), 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 (5). 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 IVs, and then discuss under what assumptions they can be considered as 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 loans farmer i utilized. 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, relatives and other channels. 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 can submit a Farm and Budget Plan stating the amounts of inputs they plan to use and the loan amount 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 (i.e., no credit constraints), this variable can be considered as 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 (i.e., such as through cooperatives). This may significantly reduce the burden of document preparation and increase the likelihood for crop insurance participation. On the other hand, the effect of 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, the Org_i variable can be a valid instrument.

Our third and final instrument is a measure of farmers' perception of 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 1. It is set to 0 otherwise. Obviously, farmers who believe crop insurance is a useful tool to manage farming risks 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 1. The summary statistics for these variables are reported in Table 2.

6. Estimation Results

We estimate (5) using a two-stage least squares (2SLS) procedure. The first-stage estimation results are reported in Table 3. All three instrumental variables have a positive sign (as expected) and a statistically significant effect on crop 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 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 fertilizers, weedicides and pesticides 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. This empirical result suggest that the input-use-increasing effect of COP insurance (i.e., from our theoretical model, this is the marginal incentives to apply more input due to the structure of the COP policy) dominates the input-use-decreasing effect of COP that comes from the traditional moral hazard effect in insurance.

Third, farmers with higher yields in the past use more fertilizers and spend more on chemicals. 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 in total. 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 fewer fertilizers and chemicals in total. 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 boost yields by using more inputs. 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 chance of crop failure (and this is also consistent with the theoretical framework developed above).

Finally, we also tested whether the insurance variable is endogenous or not using the Hausman test and results of the test indicate that we cannot reject the hypothesis that the insurance variable is exogenous. This is actually not surprising because in the Philippine 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. In light of this finding, we also estimate (5) using simple ordinary least squares (OLS) regression and the results are shown in Table 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 are 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.

6.1 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 $Credit_i$ may be considered by some as an issue. For example, farmers who don't have good outside work opportunities are more likely to be poor and borrow money, and at the same time use more inputs because they spend more time in the fields. From the discussion of the variables above, it is clear that the variable $Useful_i$ appears to require the weakest assumptions 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 only two instrumental variables in our 2SLS regression. Estimation results are reported in Tables 6 and 7. The first-stage results in Table 6 show that $Credit_i$ and $Useful_i$ still have 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 still consistent with our main results above. The insurance effects on fertilizers, weedicides and total chemical use are still positive and statistically significant; though the estimated magnitudes are slightly larger compared to the initial 2SLS results where all three instrumental variables are used.

In our second robustness check, we only include the $Useful_i$ variable as the instrumental variable in our 2SLS regression. Estimation results are reported in Tables 8 and 9. The first-stage results in Table 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 again consistent with our other results above. The insurance effect on fertilizer use is still positive and statistically significant (at the 5% level of significance), and its effect on total expenditure for chemical inputs is also positive and statistically significant (albeit at the 11% significance level). The estimated magnitudes are similar to the other robustness checks.

Another concern is that the short-run decision of choosing seed types to use (i.e., GM or not) could be endogenous as well. To address this concern, we drop the $Hybrid_i$ variable in the empirical specification and run the main regression again (see Table 10 and Table 11). The results are almost identical to the specification with the variable of $Hybrid_i$ included in the specification.

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 (5). To implement this approach, we first estimate a logit model to calculate the probability of each farmer purchasing COP insurance (e.g., the propensity score). Then, for each farmer with insurance, we match him/her with one, five, or ten uninsured farmers who have the smallest differences between their propensity scores. For each uninsured farmer, we also match him/her 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 12 show once again that having insurance significantly increases fertilizers use, weedicides use (for one to five and one to ten matching results) and the total expenditure on chemicals. In addition, the magnitudes of the effects for fertilizers and weedicides are very close to those of OLS results, but are smaller than those of 2SLS estimates. Note, however, that the insurance effect on total chemical expenditure for the PSM procedure is very similar to both the OLS and 2SLS results above. Overall, the PSM results are consistent with our main results from the 2SLS procedure and the other robustness checks conducted above.

7. Conclusion

In this study, we develop a theoretical model that examines the effect of COP crop insurance on input use application of farmers. Although there have been previous studies that investigated the effects of crop insurance on farmer input use, none have specifically focused on the input use effects of COP insurance (i.e., most previous studies only considered yield- or revenue-based crop insurance products). COP crop insurance coverage is uniquely different from yield- or revenue-based crop insurance because indemnity payments in this type of policy are explicitly linked to the total input cost of the farmer. In this theoretical model of COP insurance, we explain the incentives behind its potential effect on farmers' input use decisions (i.e., as compared to previous theoretical studies that looked at effects of yield or revenue crop insurance).

Overall, our theoretical analysis suggests that there are different channels by which COP crop insurance influence chemical input use by farmers. Consistent with previous literature that examines input use effects of yield- and revenue-based crop insurance, our theoretical model also reveal that the effect of COP insurance on input use can either be positive or negative. However, the resulting COP insurance impact on input use depends specifically on two channels: (a) the traditional moral hazard effect of insurance (i.e., an input use decreasing effect); and (b) the marginal incentives to apply more inputs due to input levels being the main determinant for expected indemnity amounts in this type of COP insurance (i.e., an input use increasing effect). In the latter channel, as COP insurance indemnity is based on the reported input use (and cost), the actual marginal cost of using additional inputs with COP insurance could be lower. Moreover, unlike past studies, the positive input-use increasing effect in our theoretical model holds, even if the COP insured farmer is risk-neutral or even if the inputs being considered has some yield-reducing features.

Based on a cross-sectional survey dataset of corn farmers in the Philippines (i.e., where COP insurance is the predominant insurance used), we then empirically illustrate the effect of a particular COP insurance product on farmers' application of chemicals in a real-life context. Using IV econometric procedures, we find that Philippine corn farmers with COP insurance coverage use more fertilizers and weedicides compared to uninsured farmers, and the total chemical expenditures of these COP farmers tend to be higher as well. Our results are also robust to several specification checks and using alternative estimation procedures. In sum, the empirical analysis indicates that the input-use-increasing effects of COP insurance (i.e., due to COP indemnities being tied to reported input levels) dominates the input-use-decreasing effects (i.e., from traditional moral hazard incentives) – resulting in a positive overall input use effect of COP insurance for this specific Philippine context.

It is important to point out that results from the theoretical and empirical analyses may have important implications for the environment. With the possibility of theoretically having a positive chemical input use effect of COP insurance (and with the strong positive effects shown in the empirical illustration), it is likely that the environment may be adversely impacted with increased COP insurance adoption. If COP insurance indeed encourages more chemical input use, then run-off of excess chemicals not absorbed by the plant may increase, and thereby exacerbate non-point source pollution in nearby waterbodies. In the Philippine context, given the empirical results above, policy makers should be cognizant of the potential "unintended" consequence of promoting COP insurance (i.e., increasing water pollution and algal blooms due to chemical runoff) and weigh this "cost" against the "benefit" of better risk protection in agriculture.

Findings from this study point to several potential directions for future research. First, in addition to the specific COP insurance product studied in this paper (i.e., based primarily on the structure of the COP insurance product in the Philippines), other variations of the COP product exists, and as such further research that examines the input use effects of these other COP insurance types should also be examined. For example, to save on the cost of verifying actual input use through hired technicians, indemnity payments in China's COP insurance program do not depend on the actual input cost incurred, but on a level exogenously set for each farmer. Therefore, the incentive from the change in the marginal cost of input use may not be present in this type of COP insurance product. Hence, it may be important to examine the input use impication of this type of insurane product. Second, the empirical analysis in this study is mainly meant to illustrate how COP insurance products can affect fertilizer and pesticide use behavior in a specific context (for a specific group of farmers and for one survey year). Therefore, it would be beneficial to empirically examine input use behavior using panel datasets with longer timeseries dimensions and larger cross-sectional scopes in order to strengthen the evidence base in the literature. Perhaps multi-year, randomized control trials (RCTs) in different countries (and for different COP products) are also possibilities for future investigation. These types of extensions to the present study are crucial, especially if COP insurance offerings increases in the future and gains more popularity worldwide.

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Figure 1. Locations of Surveyed Municipalities in the Philippines

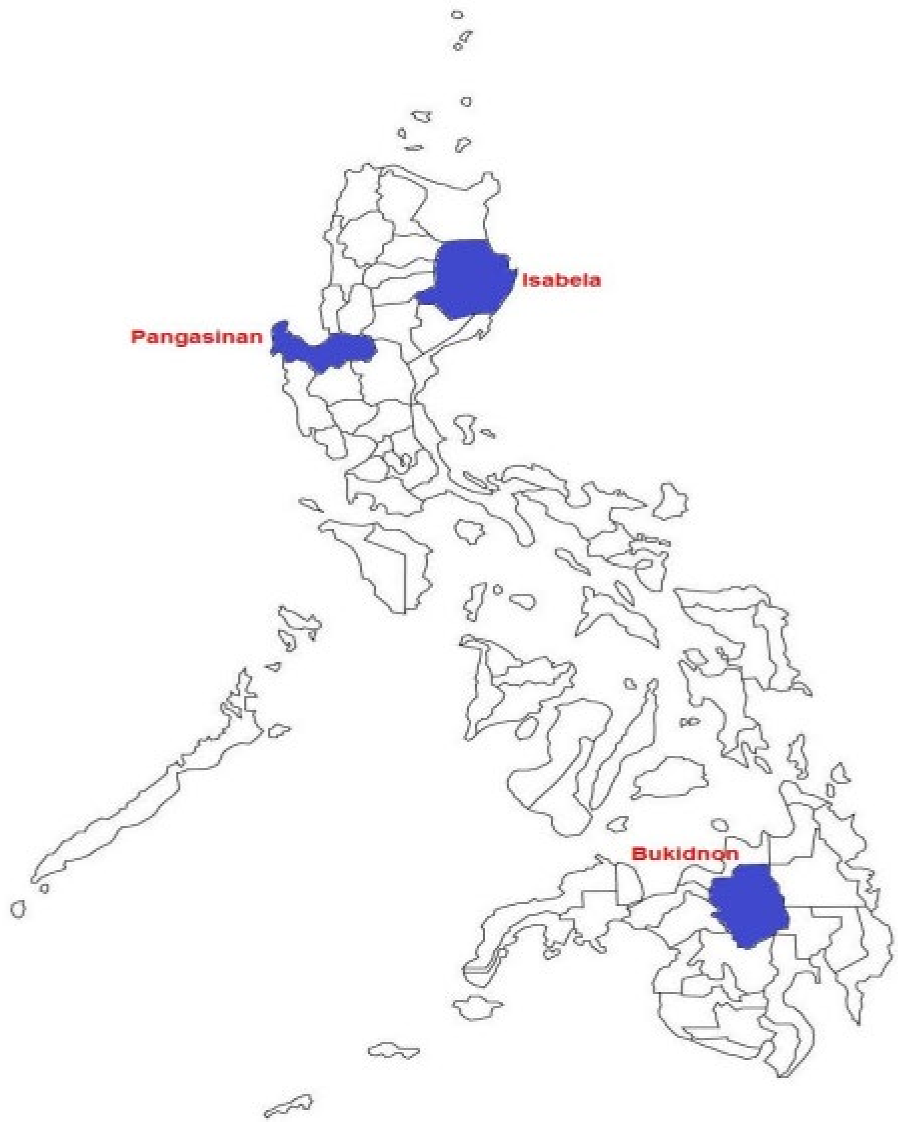

Table 1: List of Variables

Variable	Unit	Definition
Dependent variables		
Fertilizer	100 kilograms/hectare	Total kilograms of fertilizers 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 per hectare
Independent variables		
Insurance		1=having insurance and 0 otherwise
HistoricalYield	1,000 kg/hectare	Mean yield per hectare for 2010 and 2011
Hybrid		1=hybrid varieties and 0 otherwise
DistanceRoad	Kilometer	Distance to nearest road
Area	Hectare	Total area of planted fields
Livestock		1=farmer raises 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 otherwise
Isabela		1=Isabela and 0 otherwise
Pangasinan		1=Pangasinan and 0 otherwise
Instrumental variables		
Credit	10,000 PHP	Total amount of loan accessed
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: Summary Statistics of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Fertilizer	402	4.43	1.48	0.54	11
Pesticide	402	0.43	1.78	0	30
Weedicide	402	4.44	3.32	0	24
Expenditure	402	1.19	0.37	0.19	2.57
Insurance	402	0.50	0.50	0	1
HistoricalYield	386	5.07	2.47	0	18
Hybrid	402	0.71	0.45	0	1
DistanceRoad	392	0.99	1.85	0	20
Area	394	2.51	2.34	0.25	26
Livestock	402	0.15	0.36	0	1
OtherCrop	402	0.54	0.50	0	1
RiskAverse	402	0.20	0.40	0	1
Isabela	402	0.35	0.48	0	1
Pangasinan	402	0.33	0.47	0	1
Credit	401	3.06	3.65	0	34.5
Org	402	0.50	0.50	0	1
Useful	400	0.79	0.41	0	1

Table 3: First-Stage Estimation Results

Variable	*Insurance* Coef.	Std. Err.
HistoricalYield	0.0236**	0.01
Hybrid	0.0135	0.05
DistanceRoad	0.0035	0.01
Area	-0.0181*	0.01
Livestock	0.0477	0.06
OtherCrop	-0.0710	0.06
RiskAverse	-0.0325	0.06
Isabella	0.0029	0.06
Pangasinan	0.0442	0.07
Credit	0.0394***	0.01
Org	0.2749***	0.05
Useful	0.3407***	0.06
Constant	-0.0982	0.10
N of obs.	367	
F Stat. for Instruments	12.13	
Adj. R^2	0.27	

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

Table 4: Second-Stage Estimation Results

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.5177**	0.25	1.0819*	0.58	0.3514	0.37	0.1014	0.07
HistoricalYield	0.0604**	0.03	0.1417**	0.07	0.0522	0.05	0.0314***	0.01
Hybrid	0.1152	0.15	0.5154	0.34	0.0108	0.22	-0.0112	0.04
DistanceRoad	0.0821**	0.03	0.0604	0.08	-0.0051	0.05	0.0255***	0.01
Area	0.0242	0.03	-0.0494	0.07	0.0390	0.04	0.0020	0.01
Livestock	-0.0465	0.18	-0.3604	0.42	-0.2153	0.27	-0.0097	0.05
OtherCrop	-0.3765**	0.15	-0.5191	0.36	-0.1869	0.23	-0.0983**	0.04
RiskAverse	0.6468***	0.16	0.1874	0.39	0.6242**	0.25	0.1529***	0.04
Isabela	-0.5672***	0.16	-0.0280	0.39	0.4881**	0.25	-0.0990**	0.04
Pangasinan	1.0589***	0.18	-3.7181***	0.42	-0.0038	0.27	0.1469***	0.05
Constant	3.5780***	0.24	4.3732***	0.56	-0.2510	0.36	0.9663***	0.07
N of obs.	367		367		367		367	
R^2	0.3042		0.2677		0.0412		0.1989	

Overidentification Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Sargan $\chi^2(2)$	1.219	2.0667	0.9944	0.8639
P-Value	0.5436	0.3558	0.6082	0.6493
Basmann $\chi^2(2)$	1.1797	2.0048	0.9618	0.8352
P-Value	0.5544	0.3670	0.6182	0.6586

Endogeneity Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Wu-Hausman F test statistic	1.2016	1.3166	0.0453	0.0242
P-Value	0.2659	0.2520	0.8315	0.8766

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

Table 5: OLS Estimation Results

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.3071**	0.13	0.5093*	0.30	0.2807	0.19	0.0976***	0.04
HistoricalYield	0.0617**	0.03	0.1568**	0.07	0.0541	0.05	0.0306***	0.01
Hybrid	0.0861	0.15	0.5307	0.35	0.0128	0.22	-0.0182	0.04
DistanceRoad	0.0849**	0.03	0.0726	0.08	-0.0032	0.05	0.0252***	0.01
Area	0.0255	0.03	-0.0445	0.07	0.0390	0.04	0.0021	0.01
Livestock	-0.0362	0.18	-0.3069	0.42	-0.2071	0.27	-0.0116	0.05
OtherCrop	-0.3754**	0.16	-0.5425	0.36	-0.1902	0.23	-0.0964**	0.04
RiskAverse	0.6102***	0.17	0.1456	0.39	0.6225**	0.25	0.1475***	0.05
Isabela	-0.5747***	0.17	-0.0275	0.39	0.4876*	0.25	-0.1005**	0.05
Pangasinan	1.1005***	0.18	-3.7156***	0.42	-0.0092	0.27	0.1564***	0.05
Constant	3.6959***	0.23	4.5595***	0.54	-0.2278	0.35	0.9776***	0.06
N of obs.	369		369		369		369	
Adj. R^2	0.2928		0.2576		0.0148		0.1778	

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

Table 6: First-Stage Estimation Results (using *Organization* and *Useful* as the instruments)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0259**	0.01
Hybrid	0.0585	0.06
DistanceRoad	0.0102	0.01
Area	-0.0032	0.01
Livestock	0.0703	0.07
OtherCrop	-0.1158**	0.06
RiskAverse	-0.0541	0.06
Isabela	0.0714	0.06
Pangasinan	0.1214*	0.07
Org	0.2860***	0.05
Useful	0.3898***	0.06
Constant	-0.1325	0.10
N of obs.	368	
F Stat. for Instruments	9.02	
Adj. R^2	0.19	

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

Table 7: Second-Stage Estimation Results (using *Organization* and *Useful* as the instruments)

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.6962**	0.29	1.5521**	0.69	0.1240	0.44	0.1408*	0.08
HistoricalYield	0.0559*	0.03	0.1298*	0.07	0.0579	0.05	0.0304***	0.01
Hybrid	0.1133	0.15	0.5069	0.35	0.0138	0.22	-0.0114	0.04
DistanceRoad	0.0780**	0.03	0.0505	0.08	0.0000	0.05	0.0246***	0.01
Area	0.0235	0.03	-0.0532	0.07	0.0402	0.04	0.0020	0.01
Livestock	-0.0645	0.18	-0.4039	0.42	-0.1930	0.27	-0.0139	0.05
OtherCrop	-0.3695**	0.16	-0.5008	0.37	-0.1957	0.23	-0.0968**	0.04
RiskAverse	0.6573***	0.17	0.2229	0.39	0.6096	0.25	0.1546***	0.05
Isabela	-0.5660***	0.17	-0.0273	0.39	0.4870**	0.25	-0.0986**	0.05
Pangasinan	1.0618***	0.18	-3.7228***	0.43	-0.0056**	0.27	0.1484***	0.05
_cons	3.5153***	0.25	4.2143***	0.58	-0.1722	0.37	0.9521***	0.07
N of obs.	368		368		368		368	
R^2	0.2928		0.2515		0.0397		0.1962	

Overidentification Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Sargan $\chi^2(2)$	0.0048	0.4087	0.1027	0.1224
P-Value	0.9448	0.5226	0.7486	0.7265
Basmann $\chi^2(2)$	0.0046	0.3958	0.0994	0.1184
P-Value	0.9458	0.5293	0.7525	0.7307

Endogeneity Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Wu-Hausman F test statistic	2.4127	2.8534	0.1567	0.4269
P-Value	0.1212	0.0921	0.6925	0.5139

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

Table 8: First-Stage Estimation Results (using only *Useful* as the instrument)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0211*	0.01
Hybrid	0.0340	0.06
DistanceRoad	0.0223*	0.01
Area	0.0027	0.01
Livestock	0.1070	0.07
OtherCrop	-0.0461	0.06
RiskAverse	-0.0812	0.06
Isabela	0.0848	0.07
Pangasinan	0.1444**	0.07
Useful	0.4484***	0.06
Constant	-0.0676	0.11
N of obs.	368	
Adj. R^2	0.15	

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

Table 9: Second-Stage Estimation Results (using only *Useful* as the instrument)

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.7116*	0.37	1.2167	0.86	0.0173	0.55	0.1620	0.10
HistoricalYield	0.0556*	0.03	0.1383*	0.07	0.0606	0.05	0.0299***	0.01
Hybrid	0.1130	0.15	0.5131	0.35	0.0158	0.22	-0.0118	0.04
DistanceRoad	0.0777**	0.03	0.0575	0.08	0.0023	0.05	0.0241**	0.01
Area	0.0234	0.03	-0.0504	0.07	0.0411	0.04	0.0018	0.01
Livestock	-0.0659	0.18	-0.3730	0.42	-0.1832	0.27	-0.0158	0.05
OtherCrop	-0.3689**	0.16	-0.5138	0.36	-0.1999	0.23	-0.0960**	0.04
RiskAverse	0.6584***	0.17	0.1973	0.39	0.6015**	0.25	0.1563***	0.05
Isabela	-0.5660***	0.17	-0.0277	0.39	0.4869**	0.25	-0.0986**	0.05
Pangasinan	1.0617***	0.18	-3.7190***	0.42	-0.0044	0.27	0.1481***	0.05
_cons	3.5101***	0.26	4.3274***	0.60	-0.1362	0.39	0.9450***	0.07
N of obs.	368		368		368		368	
R^2	0.2913		0.2645		0.0365		0.1918	

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

Table 10: First-Stage Estimation Results (Dropping the *Hybrid* variable)

	Insurance	
Variable	**Coef.**	**Std. Err.**
HistoricalYield	0.0236**	0.01
DistanceRoad	0.0035	0.01
Area	-0.0179*	0.01
Livestock	0.0462	0.06
OtherCrop	-0.0720	0.06
RiskAverse	-0.0317	0.06
Isabela	-0.0015	0.06
Pangasinan	0.0441	0.07
Credit	0.0396***	0.01
Org	0.2738***	0.05
Useful	0.3401***	0.06
_cons	-0.0866	0.09
N of obs.	367	
F Stat. for Instruments	13.27	
Adj. R^2	0.2693	

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

Table 11: Second-Stage Estimation Results (Dropping the *Hybrid* variable)

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.5181**	0.25	1.0850*	0.58	0.3526	0.37	0.1011	0.07
HistoricalYield	0.0606**	0.03	0.1424**	0.07	0.0522	0.05	0.0314***	0.01
DistanceRoad	0.0826**	0.03	0.0623	0.08	-0.0051	0.05	0.0255***	0.01
Area	0.0262	0.03	-0.0405	0.07	0.0392	0.04	0.0018	0.01
Livestock	-0.0598	0.18	-0.4199	0.42	-0.2167	0.27	-0.0084	0.05
OtherCrop	-0.3889**	0.15	-0.5745	0.36	-0.1880	0.23	-0.0972**	0.04
RiskAverse	0.6535***	0.16	0.2172	0.39	0.6249**	0.25	0.1522***	0.04
Isabela	-0.6020***	0.16	-0.1835	0.37	0.4849**	0.24	-0.0957**	0.04
Pangasinan	1.0625***	0.18	-3.7020***	0.42	-0.0035	0.27	0.1466***	0.05
_cons	3.6713***	0.21	4.7903***	0.50	-0.2427	0.32	0.9574***	0.06
N of obs.	367		367		367		367	
R^2	0.3030		0.2631		0.0411		0.1988	

Overidentification Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Sargan $\chi^2(2)$	0.9400	1.3922	0.9890	0.9175
P-Value	0.6250	0.4985	0.6099	0.6321
Basmann $\chi^2(2)$	0.9116	1.3518	0.9593	0.8897
P-Value	0.6339	0.5087	0.6190	0.6409

Endogeneity Test

	Fertilizer	*Weedicide*	*Pesticide*	*Expenditure*
Wu-Hausman F test statistic	1.1913	1.2951	0.0454	0.0233
P-Value	0.2758	0.2559	0.8315	0.8787

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

Table 12: Propensity Score Matching Estimation Results

	Fertilizer		*Weedicide*		*Pesticide*		*Expenditure*	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
ATE （1 to 1)								
Insurance	0.2311	0.14	0.4866	0.35	0.3331	0.25	0.0776**	0.04
ATE (1 to 5)								
Insurance	0.3696***	0.13	0.4770*	0.29	0.2871	0.19	0.1070***	0.04
ATE (1 to 10)								
Insurance	0.3336**	0.14	0.5651**	0.30	0.2992	0.19	0.1044***	0.04
N of obs.	369		369		369		369	

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

APPENDIX

Claim 1: When $Q_x(x,\omega) > 0$, the first term of (4) is negative.

Proof: First, by definition, $Q(x,\omega^*) = 0.9\bar{Q}$. Therefore, $pQ(x,\omega^*) - \frac{Q(x,\omega^*)}{\bar{Q}} ax >$ $pQ(x,\omega^*) - ax$ and hence $u\left(pQ(x,\omega^*) - \frac{Q(x,\omega^*)}{\bar{Q}} ax\right) > u(pQ(x,\omega^*) - ax)$. Second, totally differentiating $Q(x,\omega^*) = 0.9\bar{Q}$ with respect to x and ω^* and rearranging terms gives $\frac{d\omega^*}{dx} = -\frac{Q_x(x,\omega^*)}{Q_\omega(x,\omega^*)}$, which is negative as we assume $Q_x(x,\omega^*) > 0$ and $Q_w(x,\omega^*) > 0$. As a result, the first term of (4) is negative. This completes the proof.

Claim 2: When $Q_x(x,\omega) > 0$, the second term of (4) can be either positive or negative.

Proof: The second term of (4) can be written as $\int_{\omega_{min}}^{\omega^*} [C(\omega)D(\omega) - E(\omega)F(\omega)]g(\omega)d\omega$, where $C(\omega) = u'\left[pQ(x,\omega) - \frac{Q(x,\omega)}{\bar{Q}} ax\right]$, $D(\omega) = pQ_x(x,\omega) - \frac{Q_x(x,\omega)}{\bar{Q}} ax - \frac{Q(x,\omega)}{\bar{Q}} a$, $E(\omega) = u'[pQ(x,\omega) - ax]$ and $F(\omega) = pQ_x(x,\omega) - a$. Therefore, the second term of (4) is a weighted sum of $C(\omega)D(\omega) - E(\omega)F(\omega)$ with $\omega \in [\omega_{min}, \omega^*]$ and weights $g(\omega)$. Below we discuss the sign of $C(\omega)D(\omega) - E(\omega)F(\omega)$ for a representative ω and show it can be either positive or negative. Then, $\int_{\omega_{min}}^{\omega^*} [C(\omega)D(\omega) - E(\omega)F(\omega)]g(\omega)d\omega$ 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 ω and negative for other values, then the weighted sum can be either positive or negative, depending on the weights assigned todifferent values of ω.

We now show for a representative ω, $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative. First, note that by defnition, for $\omega \in [\omega_{min}, \omega^*]$, $\frac{Q(x,\omega)}{\bar{Q}} < 0.9$. As a result, $0 < C(\omega) = u'\left(pQ(x,\omega) - \frac{Q(x,\omega)}{\bar{Q}} ax\right) < u'(pQ(x,\omega) - ax) = E(\omega)$

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: $D(\omega) < F(\omega) < 0$, 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 ω, $C(\omega)D(\omega) - E(\omega)F(\omega)$ 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 ω, $C(\omega) = E(\omega)$. 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: When $Q_x(x,\omega) < 0$, the first term of (4) is positive.

Proof: First, by definition, $Q(x,\omega^*) = 0.9\bar{Q}$. Therefore, $pQ(x,\omega^*) - \frac{Q(x,\omega^*)}{\bar{Q}}ax >$ $pQ(x,\omega^*) - ax$ and hence $u\left(pQ(x,\omega^*) - \frac{Q(x,\omega^*)}{\bar{Q}}ax\right) > u(pQ(x,\omega^*) - ax)$. Second, totally differentiating $Q(x,\omega^*) = 0.9\bar{Q}$ with respect to x and ω^* and rearranging terms gives $\frac{d\omega^*}{dx} = -\frac{Q_x(x,\omega^*)}{Q_\omega(x,\omega^*)}$, which is positive as we assume $Q_x(x,\omega^*) < 0$ and $Q_\omega(x,\omega^*) > 0$. As a result, the first term of (4) is positive. This completes the proof.

Claim 4: When $Q_x(x,\omega) < 0$, the second term of (4) can be either positive or negative.

Proof: The second term of (4) can be written as $\int_{\omega_{min}}^{\omega^*}[C(\omega)D(\omega) - E(\omega)F(\omega)]g(\omega)d\omega$, where $C(\omega) = u'\left[pQ(x,\omega) - \frac{Q(x,\omega)}{\bar{Q}}ax\right]$, $D(\omega) = pQ_x(x,\omega) - \frac{Q_x(x,\omega)}{\bar{Q}}ax - \frac{Q(x,\omega)}{\bar{Q}}a$, $E(\omega) = u'[pQ(x,\omega) - ax]$ and $F(\omega) = pQ_x(x,\omega) - a$. Therefore, the second term of (4) is a weighted sum of $C(\omega)D(\omega) - E(\omega)F(\omega)$ with $\omega \in [\omega_{min},\omega^*]$ and weights $g(\omega)$. Below we discuss the sign of $C(\omega)D(\omega) - E(\omega)F(\omega)$ for a representative ω and show it can be either positive or negative. Then, $\int_{\omega_{min}}^{\omega^*}[C(\omega)D(\omega) - E(\omega)F(\omega)]g(\omega)d\omega$ can either be positive or negative, depending on the specification of $g(\cdot)$. This is because as long as $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive for some values of ω and negative for other values, then the weighted sum can be either positive or negative, depending on the weights assigned todifferent values of ω.

We now show for a representative ω, $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative. First, note that by defnition, for $\omega \in [\omega_{min},\omega^*]$, $\frac{Q(x,\omega)}{\bar{Q}} < 0.9$. As a result, $0 < C(\omega) = u'\left(pQ(x,\omega) - \frac{Q(x,\omega)}{\bar{Q}}ax\right) < u'(pQ(x,\omega) - ax) = E(\omega)$ because $u' > 0, u'' < 0$. In addition, $F(\omega) = pQ_x(x,\omega) - a < 0$, as we assume

$Q_x(x,\omega) < 0$. Then, depending on the relationships among $D(\omega)$ and 0, we have the following two cases.

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

Case 2: $D(\omega) < 0$, then $C(\omega)D(\omega) - E(\omega)F(\omega)$ can be either positive or negative. If we have $F(\omega) < D(\omega)$, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive. If $F(\omega) > D(\omega)$, the sign of $C(\omega)D(\omega) - E(\omega)F(\omega)$ is ambiguous.

These two cases show clearly that for a representative ω, $C(\omega)D(\omega) - E(\omega)F(\omega)$ 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 ω, $C(\omega) = E(\omega)$. In case 2, if $F(\omega) < D(\omega)$, $C(\omega)D(\omega) - E(\omega)F(\omega)$ is positive. If $F(\omega) > D(\omega)$, the sign of $C(\omega)D(\omega) - E(\omega)F(\omega)$ is negative. Results for other cases remain the same. This completes the proof.