Estimating the Effect of Crop Insurance on Input Use When Insured Farmers are Monitored

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Abstract

Monitoring is one way to alleviate the moral hazard problem rampant in most crop insurance programs. Lacking explicit data on monitoring, we test the effectiveness of monitoring on reducing moral hazard behavior indirectly. We first propose a theoretical model that takes into account several features of the Philippines crop insurance program – the empirical setting of interest. Our model predicts that if monitoring is effective, then crop insurance should have a positive effect on the use of certain inputs. Our empirical analysis of a survey dataset of corn farmers in the Philippines confirms this theoretical prediction and lends empirical support to the hypothesis that monitoring is effective in reducing moral hazard behavior by the farmers.

Introduction

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

However, implementing the crop insurance programs in a sustainable and effective way is challenging. Once farmers get insured, they game the system to their advantage. One problem is moral hazard. As insured farmers will be compensated if they have losses, they tend to exert less effort during production (i.e. use less input). Smith and Goodwin (1996) showed that insurance purchase made farmers use fewer chemical inputs based on a survey of Kansas dryland wheat farmers in 1992. Babcock, and Hennessy (1996) pointed out that nitrogen fertilizer and insurance are substitutes, so farmers under insurance coverage are likely to use less nitrogen. Quiggin, Karagiannis and Stanton (1993) found negative but insignificant effect of insurance on input use. Goodwin, Vandeveer, and Deal (2004) showed that in the Upper Great Plains, the rising in adoption of insurance came with a decrease in fertilizer and chemical expenditures by wheat and barley farmers.[1]

Some strategies have been proposed and implemented to fight against moral hazard. One strategy is to base premiums on past performance. In the U.S. crop insurance markets, as pointed out by Weber, Key, and O'Donoghue (2015), the potential effect of moral hazard is restrained by the structure of insurance contract that sets premiums and guarantee yields based on yield histories. A claim in one year increases the premium and decreases the guaranteed yield levels for the following years. For another example, Dionne et al. (2005) showed that a change in auto insurance regulation that increased the premiums charged to drivers with worse records reduced accidents. The second strategy is to increase the co-pay rates. As people's share of losses increases, they are motivated to not engage in risky behaviors. For example, Chiappori, Durand, and Geoffard (1998) studied a change in French health insurance from a full coverage to a ten percent copayment, and showed that the copayment decreased doctor home visits. Yet another strategy is monitoring. As moral hazard arises because of hidden actions, if insurers can monitor insureds' behaviors, the moral hazard problem can be curbed. Bellemare (2010) showed that, for a sample of contract farmers in Madagascar, the number of visits by agricultural technicians had a positive and statistically significant effect on production.

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

Frisvold (1994) showed that supervision needs to be employed to increase hired labor productivity based on data from an Indian village. Jacoby and Mansuri (2009) found that yields on the plots cultivated by supervised tenants were significantly higher than those cultivated by unsupervised tenants.

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

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

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

Background

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

According to the Rural Poverty Report (2011) of the International Fund for Agricultural Development (IFAD), weather shock is the major factor that contributes to impoverishment in the Philippines. Farmers could mitigate the impact of weather shock in several ways. They can adopt on-farm strategies to alleviate production risks, or purchase crop insurance, which is a recognized institutional tool to address shocks in agricultural production. Crop insurance is especially suitable during recent years when farmers have been confronted with new challenges imposed by climate change. The

Philippines has a tropical maritime climate and it is more prone to natural disasters, such as floods and typhoons. As a result, this country is particularly vulnerable under climate change. One adverse weather event can instantly cause severe losses and poor farmers are usually unable to recover from these losses. These situations give rise to the main theme of crop insurance programs in the Philippines, which is to make sure that farmers are able to restart production and rebuild their livelihood after severe losses.

The Philippine Crop Insurance Corporation (PCIC)

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

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

The PCIC Corn Insurance Program

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

PCIC also classifies corn producers who buy coverage into two categories: (a) the borrower client, and (b) the self-financed client. The borrower client secures a production loan from a formal lending institution, and also purchases crop insurance. As mentioned above, formal government-sponsored lending institutions typically require purchase of crop insurance for farmers wanting to acquire loans from this source. The self-financed client, however, does not have loans from formal sources and only purchases crop insurance from PCIC.[3]

Farmers can purchase insurance through several different venues, such as lending institutions where they obtain their loans, the PCIC regional office or other PCIC authorized underwriting agents. Farmers who want to get insured have to submit application before the fifteenth day after planting. The insurance coverage (i.e., the

[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 asset, 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., 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.

liability amount) for corn is primarily determined based on the total cost of production inputs, as indicated in the Farm Plan and Budget that the farmers are required to submit upon application. The farmer also has the option to include an additional cover amount of up to 20% of the value of the expected yield, with the approval of the PCIC. However, it should be noted that the PCIC corn insurance product is subject to the following liability ceilings: (a) PHP 40,000/USD 948[4] per hectare for hybrid and GMO corn varieties, and (2) PHP 28,000/USD 664 per hectare for open-pollinated varieties.

Reyes et al. (2015) points out that premium rates for corn insurance in the Philippines are largely based on historical data on damage rates (i.e., the ratio of indemnity to liabilities, which is also called the loss cost ratio) at the provincial level. Premium rates for the corn insurance product vary depending on: geographical location (i.e., different rates for different provinces), the type of insurance cover (natural disaster vs. multi-risk), and cropping season (wet vs. dry). Provinces are typically classified as low, medium or high risk depending on historical damage rates. Premium rates are higher for multi-risk cover (as compared to the natural disaster) because it covers losses from pest and diseases in addition to losses from weather events. Wet season cropping is also associated with higher premium rates (relative to the dry season cropping) because wet season is when typhoons and floods usually occur. It should be noted, however, that PCIC premium rates have not been regularly updated over time (Reyes et al., 2015, p. 42). Since 1981, premium rates charged to farmers were only updated once in 2005.

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

The Philippine government heavily subsidizes corn insurance premiums. The government pays more than 50% of the total insurance premium for corn. Lending institutions also share a portion of the premium if the insured farmer borrows from them (i.e., the borrower client). Therefore, the borrower clients' premiums are shared among the lending institution, the government, and the farmers themselves. The self-financed clients' premiums, on the other hand, are only shared with the government. But note that the total premium rate is typically the same for both the borrowing and the self-financed farmers.[5] In addition, the government's share is also the same for both types of farmers. This arrangement means that self-financed clients have to pay an additional amount of premium (relative to the borrower clients), which is equivalent to what would have been assumed by lending institutions if they were borrower clients.

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

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[5] 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/.

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

When a loss event occurs due to a covered cause of loss, farmers need to file a Notice of Loss to the PCIC regional office. A team of adjusters will then verify the claim and only a loss over 10% would make the insured farmers eligible for indemnity payments. The insurance policy pays out indemnity in proportion to the percentage of loss due to specific insurable causes (as specified by the adjuster).

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

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

Model

In this section, we propose a theoretical model that takes into account many of the features of the Philippines crop insurance program, and predict the relationship between insurance and input use when the insured farmers are monitored by technicians from the insurance agency during the production season. Formally, assume a representative farmer owns one hectare of arable land.[6] The production function for the farmer takes the form of $f(x)$ with $f' > 0$ and $f'' < 0$, where x denotes the inputs used. The farmer has a ρ $(0 < \rho < 1)$ chance of encountering a risk event during the production season that will reduce his harvest from $f(x)$ to $\theta(x)f(x)$, where $0 < \theta < 1$ and $\theta'(x) > 0$. Due to its geographical characteristics, the Philippines is prone to natural calamities such as typhoons, floods and volcanic eruptions. Thus, farming decisions have little impact on the chance for these disasters to happen. Also, farms in the Philippines are usually small and hence the outbreak of pest infestation is mainly influenced by factors uncontrollable to the farmers, as plant pests and disease infestation usually occur in epidemic proportion. For these reasons, we assume that the chance for a disaster to happen, ρ, is exogenous to the farmer. On the other hand, the amount of yield loss when a disaster happens can be affected by the amount of inputs used. For instance, fertilizers increase plant vigor and vitality so its natural capacity to combat pests and diseases improves. Moreover, both herbicides and pesticides decrease potential yield damage from pests. Therefore, we allow θ to be an increasing function of x in our model.

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

The farmer is risk averse. His preference is characterized by the utility function $U(I) = -I^{-1}$ if $I > 0$ and $U(I) = -\infty$ if $I \leq 0$, where I is wealth. This is the power utility function with the constant relative risk aversion parameter being 2.[7] Without insurance, the farmer's objective is to maximize the following expected utility function,

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

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

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

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

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

Equation (2) differs from (1) only in the second part.[8] When a disaster hits and $[1 - \theta(x)]$ of the yield is lost, the farmer will be reimbursed for the same proportion of his input cost, reducing the cost from wx to $\theta(x)wx$. The optimal solution to farmer's maximization problem (2) is denoted as x_I^*.

Furthermore, we consider two cases. Under the first case, we assume that the marginal effect of input on yield is larger when there is no disaster than when a disaster hits, that is,[9]

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Data

The data set used in this study comes from a farm-level survey conducted in 2013 under a program called "Improving the Agricultural Insurance Program to Enhance Resilience to Climate Change." This program was administered by the Southeast Asian Regional Center for graduate study and research in agriculture (SEARCA). This survey covers three major corn growing provinces in the Philippines: Isabela, Pangasinan and Bukidnon. Farm households were selected for the survey using the multi-stage stratified random sampling approach. Two municipalities from each province were chosen based on the area devoted to corn production and the number of producers enrolled in PCIC corn insurance program. The data on the area devoted to corn and the number of insured producers were obtained from the Bureau of Agricultural Statistics (BAS) and PCIC, respectively. In each sampled municipality, two villages with the largest numbers of insured farmers were chosen, and then, corn farmers in each village were stratified into insured and non-insured for the wet season (June-December) of the year 2012. In each stratum, 213 farmers were chosen randomly. The list of insured corn farmers was provided by PCIC and the list of non-insured farmers were obtained from village heads. A total of 426 corn producers were surveyed. The questionnaire elicits a wide range of farmers' information including the farmer's demographic background, socio-economic conditions, inputs used, farming and management practices, and some psychometric measures (such as indicators of cognitive ability and cautiousness).

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

Empirical Strategy

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

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

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

Below we discuss the definition of each variable and the reasons to include them in the regressions.

Since each farmer has land with different quality, faces different weather conditions, and uses different technology, we include the average yield per hectare of the two most recent years, that is, 2010 and 2011, ($HistoricalYield_i$) in the regressions to control for the effect of unobserved individual heterogeneity that are not captured by the province dummies on input use.[10]

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

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

The total farming area is denoted as $Area_i$. It is expected that large farms are associated with more farming assets, so this variable is used to examine the wealth effect on input use. Also, the area variable reflects the scale of the farm and captures any returns to scale effect on input use.

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

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

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

Identification

One challenge in estimating (12) is that the insurance variable, $Insurance_i$, might be endogenous. For example, a farmer may possess some private information that his fields have a high probability of being struck by pests in the coming year. As a result, he purchases insurance and also uses more pesticides to minimize the expected loss. To correct for this potential endogeneity bias, we use the instrumental variable approach. For a variable to be a good instrument, it has to satisfy two conditions. First, it has to be excluded from (12), that is, it should have no effect on input use once X_i is controlled for. Put in other words, it needs to be uncorrelated with the error term u_i in (12). Second, it has to be correlated with the potentially endogenous variable, that is, the insurance variable. Although the second condition can be tested directly by examining the first stage estimation results from the two-stage least squares IV estimation, the first condition can only be tested indirectly through the overidentification test. Below, we identify three variables in our dataset that can potentially be used as instrumental variables and then discuss under what assumptions they are valid instruments. We also perform statistical tests to examine the validity of these instruments.

Our first instrumental variable is $Credit_i$, which is the total amount of loan farmer i borrows. One section in the survey is on sources of capital. It asks farmers to report the sources and the amount of their borrowings. The sources can be official or private lending institutions, banks, relative and others. In the Philippines, those who borrow from official lending institutions are required to purchase insurance and some farmers who borrow from other channels are also required to purchase insurance. Therefore, the amount of loan certainly has an impact on the likelihood of purchasing insurance. On the other hand, if a farmer cannot borrow all the money he needs to purchase inputs, then the more he can borrow, the more inputs he will use. In the Philippines, this is unlikely to be the case, at least for those farmers who borrow from official lending institutions. For these farmers, they submit a Farm and Budget Plan stating the amounts of inputs they plan to use and the amount of loan they need to purchase these inputs as part of their loan application. As the government has been very supportive of farming, it usually approves the requested amount of loan. Therefore, under the assumption that farmers have no problem borrowing the money needed to purchase inputs, this variable is a valid instrument.

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

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

All the variables discussed in this section, together with their definitions, are listed in Table 1. The summary statistics for these variables are reported in Table 2.

Estimation Results

We estimate (12) using two-stage least squares (2SLS). The first-stage estimation results are reported in Table 3. All of the three instrumental variables have a positive (as expected) and statistically significant effect on insurance purchase. The F statistic for the joint hypothesis that none of the three instrumental variables has any effect on insurance purchase is larger than 10, indicating that we can reject the hypothesis that the IV regression is weakly identified. This verifies that our instruments are correlated with the potential endogenous variable.

The second-stage estimation results are reported in Table 4. Several results are worth discussing. First, the overidentification test results indicate that we cannot reject the hypothesis that our instruments are valid. Second, crop insurance is found to have a positive effect on the use of fertilizer, weedicide and pesticide as well as the total expenditure on chemicals. Three out of the four estimated effects are statistically significant. The magnitudes of the effects are not small. For example, insured farmers use 53 more kilograms of fertilizers per hectare than uninsured farmers. This is equivalent to about 12% of the average amount of fertilizers used by farmers in the dataset. These results lend empirical support to our Theorem above and show that when insured farmers are being monitored, there is no room for moral hazard behavior and they are willing to spend more on inputs. Note that the reason that the effect of insurance is not significant on pesticides is explained in the model section. It is because the positive effect of insurance on input use is predicted for more yield-enhancing rather than damage-control inputs.

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

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

Finally, we also tested whether the insurance variable is endogenous or not using the Hausman test and results there indicate that we cannot reject the hypothesis that the insurance variable is actually exogenous. This is actually not surprising because in the Philippines crop insurance market, many farmers do not purchase insurance voluntarily. Those farmers who borrow from official lending institutions are required to purchase insurance and some farmers who borrow from other channels are also required to purchase insurance. Therefore, (12) is also estimated using OLS and the results are collected in Table 5. The OLS results are very similar to the 2SLS results, both in terms of statistical significance and magnitudes of the effects with the only exception that insurance is found to have a smaller effect on fertilizers and weedicides. But the absolute value of the estimates are still not trivial and statistically significant. For example, the 2SLS results show that on average insured farmers use 53 more kilograms of fertilizers per hectare than uninsured farmers, while the OLS results show insured farmers use 30 more kilograms of fertilizers per hectare than uninsured farmers.

Robustness checks

Although the overidentification test and the first-stage F test results above suggest that we cannot reject the hypothesis that the three instrumental variables used are valid, we also cannot rule out the possibility that any or all of them are invalid. The variable $Credit_i$

causes some concern. For example, farmers who have loans can be under higher pressure to produce more corn. However, from the discussion of those variables above, it is clear that the variable $Useful_i$ appears to require the weakest assumptions to be used as a valid instrumental variable. Therefore, in our first robustness check, we drop $Credit_i$ and use both the $Organization_i$ and the $Useful_i$ variables as the instrumental variables in our instrumental variable regression. Estimation results are reported in Tables 2.6 and 2.7. The first-stage results in Table 6 show that $Credit_i$ and $Useful_i$ still has positive and statistically significant effects on insurance purchase. The F statistic for the joint hypothesis that neither of the two instrumental variables has any effect on insurance purchase is very close to 10 (at 9.7), implying that the IV regression is not weakly identified. The second-stage estimation results are consistent with our main results above. The insurance effects on fertilizer, weedicide and total chemical use are positive and statistically significant The estimated magnitudes are slightly larger compared to the 2SLS results when all three instrumental variables are used.

In our second robustness check, we use only the $Useful_i$ variables as the instrumental variable in our instrumental variable regression. Estimation results are reported in Tables 2.8 and 9. The first-stage results in Table 8 show that $Useful_i$ has a positive and statistically significant effect on insurance purchase, rejecting the hypothesis that this IV regression is weakly identified. The second-stage estimation results are consistent with our main results above. The insurance effect on fertilizer use is positive and statistically significant at 5% and its effect on total expenditure for chemical inputs is positive and statistically significant at 11%. The estimated magnitudes are similar to previous robustness check.

Another concern is that the short-run decision of seed choice could be endogenous as well. To address this concern, we drop the $Hybrid_i$ variable and run the main regression again (see Table 10 and Table 11). The results are almost identical to the specification with the variable of $Hybrid_i$.

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

The PSM estimation results in Table 12 show once again that having insurance significantly increases fertilizer use, weedicides use (for one to five and one to ten matching results) and total expenditure on chemicals. In addition, the magnitudes of the effects for fertilizers and weedicides are very close to those of OLS but smaller than those of 2SLS. The insurance effect on total chemical expenditure is very similar to both OLS and 2SLS results. Therefore, we conclude that the PSM results are consistent with our main results above.

Conclusion

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

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

Several related questions remain unanswered. First, though monitoring can reduce the cost associated with moral hazard, it is costly in itself. Therefore, the natural question to ask next is whether monitoring can pay for itself. Second, as mentioned above, there are other ways to curb the moral hazard problem such as setting premiums based on past claim histories or decreasing the indemnity payments as a percentage of the losses. It would be interesting to compare all these alternative strategies to curb moral hazard in terms of effectiveness and costs. These are left for future research.

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Table 1 List of Variables

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

Table 2 Summary Statistics

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

Table 3 First-Stage Estimation

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

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

Table 4 Second-Stage Estimation

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

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

Table 5 Ordinary Least Square Estimation

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

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

Table 6 First-Stage Estimation (using *Organization* and *Useful* as the instrument)

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

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

Table 7 Second-Stage Estimation (using *Organization* and *Useful* as the instrument)

	Fertilizer		***Weedicide***		***Pesticide***		***Expenditure***	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Insurance	0.6960***	0.29	1.4883**	0.67	0.1600	0.43	0.1435**	0.08
HistoricalYield	0.0566*	0.03	0.1084	0.08	0.0529	0.05	0.0254***	0.01
Hybrid	0.1061	0.15	0.4747	0.35	0.0062	0.22	-0.0207	0.04
DistanceRoad	0.0770**	0.04	0.0687	0.08	0.0090	0.05	0.0239***	0.01
Area	0.0221	0.03	-0.0550	0.07	0.0418	0.04	0.0004	0.01
Livestock	-0.0683	0.18	-0.5141	0.43	-0.2204	0.27	-0.0294	0.05
OtherCrop	-0.3648**	0.16	-0.4462	0.37	-0.1969	0.23	-0.0891**	0.04
RiskAverse	0.6587***	0.17	0.2141	0.39	0.6121***	0.25	0.1568***	0.04
Isabella	-0.5742***	0.17	-0.0171	0.39	0.4701*	0.25	-0.1085***	0.05
Pangasinan	1.0507***	0.19	-3.6476***	0.43	0.0109	0.28	0.1505***	0.05
_cons	3.5257***	0.25	4.3190***	0.59	-0.1692	0.38	0.9848***	0.07
N of obs.	364		364		364		364	
R^2	0.2866		0.2543		0.0389		0.1887	

Overidentification test		P-Value		P-Value		P-Value		P-Value
Sargan $\chi^2(2)$	0.0016	0.9676	0.554	0.4567	0.1065	0.7441	0.0303	0.8619
Basmann $\chi^2(2)$	0.0016	0.9682	0.5365	0.4639	0.103	0.7482	0.0293	0.8642
Endogeneity Test		P-Value		P-Value		P-Value		P-Value
Wu-Hausman F test statistic	2.6264	0.106	2.2636	0.1333	0.1023	0.7492	0.4052	0.5248

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

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

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

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

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

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

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

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

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

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

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

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

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

Table 12 Propensity Score Matching Estimation

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

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