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Evidence of Moral Hazards in Crop Insurance in Northeast China

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Abstract

The article evaluates the extent of moral hazards in the government-subsidized crop insurance in North-east China. 356 maize-growing households were surveyed. The households' behavioral changes in cultivating maize were examined by the propensity-score matching method. The research found that households with crop insurance put 133.03 kilograms more base fertilizer, but 144.49 kilograms less top-dressing per hectare, and use herbicide more often by 0.3 times. Higher doses of base fertilizer and herbicide which are convenient but not efficient in practice are likely to make farmers less care about the maize. Therefore, we consider the abuses of those chemicals as evidence of moral hazards in the current term of crop insurance. In order to mitigate moral hazards and improve the efficiency of the crop insurance program, more specific claimable causes of loss and higher protection level per hectare are suggested.

Keyword: Crop insurance, Moral hazards, Behavior, Maize, Agriculture

INTRODUCTION

As one of a few countries with a large variety of destructive natural disasters, Chinese agricultural society has been facing enormous challenges from extreme weather conditions due to the progress of global warming. According to World Bank (2007), North-east China is one of the riskiest regions in China, and severe weather conditions are reported more often in recent years. It experienced an average annual damaged acreage of 6.3 million out of 25 million hectares of total sown acreage during the period from 1978 to 2017 due to the extreme weather. The worst two years are all after 2007, of which the annual damaged acreages were more than 10 million hectares (NBSC, 2018). The increasing risks of more frequent server weather conditions may have significant impacts on many Chinese farmers' production activities.

China has about 500 million people involved in agricultural labour and most of them are small and marginal farmers. The vast majority of farmers grow rainfed crops and are therefore particularly vulnerable to the vagaries of the weather. One of the major rainfed crops is maize, which contributes the highest portion at 22% out of total sown acreage (37 million hectares) in 2014 (NBSC, 2018). The damages caused by the extreme weather could significantly reduce many farmer's incomes and consequently discourages risk-averse individuals engage in a risky farming business, which might hinder the overall growth of the agriculture industry (Swiss Re, 2013).

In order to mitigate increasing risks of more frequent server weather conditions to individual farmers and stabilize the growth of the agriculture sector, the Chinese central government introduced the agricultural insurance scheme with heavy subsidies in 2004. The total amount of subsidies for Chinese maize farmers has been significantly increasing over the years, from CNY 5.33 billion (equivalenting to USD 0.68 billion) in 2007 (Zhong & Huang, 2015) to CNY 13.6 billion in 2016 and 14.7 billion in 2017 (about USD 2.1 billion) (WTO, 2018). The insurance premium subsidies are mainly for yield-based multi-perils crop insurance. Weather-index crop insurance and other forms are only found in a few pilot projects. Wang et al. (2011) reported that the central and provincial governments subsidized 50% of the insurance premium, while the shares of subsidies from municipal and county governments varied between 10% and 30%. Thus, the total share of subsidies from the four levels of government was between 60% and 80%, and farmers had to pay the remainder of the premium for participating in the program.

Although the yield-based crop insurance assists farmers to manage risks of yield losses, it may lead to moral hazards including poor farm management, lack of efforts in protecting the crops while encouraging farmers to seek insurance compensation instead. Some studies in the U.S. have found moral hazards associated with crop insurance programs, but the results were inconclusive. Horowitz and Lichtenberg (1993) mentioned that insurance increased the risk of moral hazards of maize farmers in the Midwest U.S. by reducing their responsibilities for the use of chemicals in crop management. Those purchasing insurance spent more on chemicals and applied more nitrogen, herbicides and pesticides per hectare. Babcock and Hennessy (1996) demonstrated that Kansas wheat producers who bought crop insurance tended to use less fertilizer and chemicals than those with no crop insurance. Therefore, it is important to measure and control the potential impacts of moral hazards in order to enhance the efficiency of crop insurance in China.

Most of the previous studies in China focused on the theoretical perspectives including the necessity and potential effects of implementing crop insurance. Yang et al. (2010) claimed the existence of serious moral hazards due to information asymmetry issues in China without specifying any evidence. Ke et al. (2015) stated that the deductible of the insurance can help to avoid moral hazards while evaluating the welfare effects of crop insurance in Central China. So far, there has been no study reporting signs of the moral hazards from crop insurance in China. The increasingly popular of crop insurance in China and the continuous rise of the government insurance premium subsidies indicate the importance of evaluating the extent of the moral hazards and finding out solutions to mitigate those risks in order to enhance the effectiveness of insurance subsidy programs. Therefore, this study aims to fill the gap in the research of moral hazards associated with crop insurance by evaluating the extent of the moral hazards and investigating farmers' intended risk behaviour towards a crop insurance program.

DATA AND METHODOLOGY

The dominant crop insurance for maize is multi-peril crop insurance, but details of compensation policies vary across provinces. Hei Long Jiang province is an important grain-producing region in North-east China. Maize is the most popular grains cultivated in the region (5.2 million hectares in 2016, 61% of the grain farmland) (NBSC, 2018). As at 2016, the yield-based multi-peril crop insurance was applied for three crop types including maize, soybean and rice in order to indemnify losses from all kinds of natural biological disasters and accidents as well as compensate differences between actual yields and a specified average yield of the county (70% of the 5-year average yield) in Hei Long Jiang province. The survey from this study was conducted in Lin Kou county of the province from June to September 2017. This county has approximately 80,000 families in the countryside with half of them being maize farming households and centralizing in 170 villages (NBSC 2018). This study uses the production data in 2016 collected by using survey questionnaires for 356 maize farming households in 30 villages from 7 out of 11 towns.

Among 356 surveyed households, 6 households which had the total acreage in 2016 greater than 40 hectares were considered as outliners of the dataset and being eliminated from further analysis. The remaining 350 households have an average cultivated acreage of 8.98 hectares with all the individual household's acreages being no more than 30 hectares. Based on the refined dataset, this study found that 71% of these 350 households (equivalent to 249 households) bought the crop insurance in 2016. Maize was the dominant crop type of households in the surveyed sample, accounting for about 77% of the total acreage. The rest crops were mainly soybean (15%), rice, white melon, and red bean. A summary of the dataset is shown in Table 1.

Table 1: Descriptive statistics

Variables	Obs.	Mean	Standard Deviation	Min.	Max.
Age of decision maker in a household	350	46.99	9.58	25	82
No. of family members per households	350	4.03	1.30	1	8
Education level of the decision maker in a household	346	8.35	1.97	0	15
Cultivated acreage (ha)	305	8.98	5.25	1	32
Maize specific information					
Yield per ha (KG)	343	9,018.48	1,685.45	3,500	12,500
Income per ha	339	6,881.94	1,950.00	2,449	12,500
Land rent per ha	300	4,280.20	1,119.44	1,500	7,500
Cost of Seed per ha	344	992.37	459.19	142	3,600
Cost of Extra Labor per ha	298	410.02	853.51	0	12,000
Quantity of base fertilizer (KG per ha)	324	545.96	187.85	100	850
Quantity of top dressing (KG per ha)	320	286.79	276.68	0	4,200
Frequency of herbicide	339	2.45	0.55	1	4
Frequency of foliar fertilizer	289	0.85	0.44	0	3

Notes: for Table 1: among 356 collected questionnaires, there are missing data of some variables. The difference between the numbers of observations and 356 represents the amount of missing data of each variable.

In order to accurately estimate the impact of crop insurance on a farmer's behaviour, the difference between the outcomes from the insurance buyers and the outcomes from the same farmers who do not buy the insurance (the counterfactual) need to be measured. Let $Y_{i,t}$ be an outcome when a farmer bought the insurance (treated state), $Y_{i,t}$ be the outcome when a farmer did not buy the insurance (untreated state), and D is a dummy variable indicating crop insurance buying decision (D= 1 for buying the insurance). The observed outcome is,

$$Y_i = DY_{i,t} + (1 - D)Y_{i,u}$$

This impact is known as the average treatment effect on the treated (ATT) which is defined as:

$$ATT_i = E\left(Y_{i,t} - Y_{i,u} \middle| D = 1\right) = E\left(Y_{i,t} \middle| D = 1\right) - E\left(Y_{i,u} \middle| D = 1\right)$$

But in reality, the outcome of insurance buyers who had not treated does not exist $\mathrm{E}\left(\mathrm{Y}_{\mathrm{i,u}} \middle| \mathrm{D} = 1\right)$. Only outcomes of the farmers who did not buy insurance are observable $\mathrm{E}\left(\mathrm{Y}_{\mathrm{i,u}} \middle| \mathrm{D} = 0\right)$. If decisions of buying the insurance are randomly assigned, the decision variable would be statistically independent of the outcomes $(\mathrm{Y}_{\mathrm{i,t}}, \mathrm{Y}_{\mathrm{i,u}})$. Then, $\mathrm{ATT}_{\mathrm{i}}$ is identical to the expected impact of the insurance on randomly drawn farmers,

$$ATT_i \quad ATT_i = E\left(Y_{i,t} - Y_{i,u} \middle| D = 1\right) = E\left(Y_{i,t} - Y_{i,u}\right)$$

$$= E\left(Y_{i,t} \middle| D = 1\right) - E\left(Y_{i,u} \middle| D = 0\right)$$

However, the randomization of the insurance buying decision is not met in the real case since both observed and unobserved characteristics of farmers influence the insurance buying decision and the outcomes of interest. Therefore, using the equation above in the estimation with non-randomization nature of the decision-making process will lead to biased results, which is called selection bias. In order to minimize the selection bias in the impact analysis, we need to find the farmers who did not buy the insurance but had a similar set of observed characteristics X with the insurance buyers as the counterfactuals. The observed characteristics X are multi-dimensional and cannot be directly aligned. Rosenbaum and Rubin (1983) developed techniques to solve this problem called Propensity Score Matching (PSM) method. The method is used to transform the multi-dimensions of characteristics X to a single dimension representing the probability of treatment P(X), named as the propensity score, where $\mathrm{P(X) = Pr\ ((D = 1|X), P(X) \in [0,1]}$, and to match the treated and control groups based on the propensity score. The insurance buyers and non-buyers with similar Propensity Score or P(X) to buy are matched for further comparisons. After being matched by the PS, $\mathrm{ATT_i}$ can be obtained with minimized selection bias,

$$ATT_i = E\left(Y_{i,t}\middle|D = 1, P(X)\right) - E\left(Y_{i,u}\middle|D = 0, P(X)\right)$$

In the first step of the PSM implementation, a logit regression model of insurance buying decision has been estimated to generate propensity scores for all farmers including both insurance buyers and non-buyers in the sample. There are five variables including age, education of household's decision maker, the share of non-farming income in total income of the household, rent of land, and the expected loss ratio (the expected insurance compensation, details in Appendix A, divides the expected insurance premium) are chosen to generate the Propensity Score as illustrated in Table 2. The five variables are proxies to differentiate farmers' rationality, land quality and expected payoffs of insurance, which are important factors influencing an individual's insurance buying decision.

Table 2: Variables in the Propensity Score Matching

Variables	Description
Age	the age of the household's decision maker;
Education	the education level of the household's decision maker in a number of years;
Non-farming income	the share of non-farming income in total income of the household;
Land rent	the rental fee of the land paid by the household;
Expected loss ratio	the expected loss ratio (the expected insurance compensation divided the expected insurance premium);

In the second step of the PSM implementation, the insurance buyers are matched with non-buyers. There are several techniques to match the insurance buyers with non-buyers, such as One-to-one matching with replacement, 5-Nearest neighbours matching, Radius matching and Kernel matching methods. However, It is important to test the matching quality to see whether the mean of all observable variables between the insurance buyers and their counterfactual are not significantly different. After matching, this study estimates the impact of the insurance program (ATT) using the previous equation. Evidence of moral hazards is indicated by changes in farm management practices as the usage of seeds, fertilizers and herbicides, and the output yield.

The usage of the seed is indirectly measured by the cost of seed per hectare, which a multiplication of cost per kilogram times kilogram per hectare (instead of the quantity) because different size of maize seeds causes the different quantity of the seed per hectare, different seed brands cost differently. Base fertilizer and top dressing fertilizer are directly measured by the weight. The herbicide and foliar fertilizer are simply indicated by frequencies of use due to the complexity of details. The output yield is directly measured by kilogram per hectare. As pesticide and insecticide are not normally applied in the region unless there is information about the emergence of bio-hazards, we do not count them in the study.

Although the PSM implementation is an effective tool to control the observable selection bias, the process of insurance buying decision may relate to unobserved variables that influence the outcomes of moral hazards (DiPrete & Gangl, 2004). Although the PSM results provide important information about the sign as well as the strength of the relationship between the insurance and outcomes of the moral hazards, the interpretation of this relationship can be influenced by unobserved variables. This study uses the Rosenbaum bounds sensitivity analysis (Rosenbaum, 2002) to assess the sensitivity of the PSM results in potential hidden bias. The Rosenbaum bounds sensitivity analysis evaluates how strong the un-observed variables' influence on the insurance buying decision is, in order to address the implications of the PSM implementation. DiPrete and Gangl (2004) comment that the Rosenbaum bounds analysis can provide reasonable confidence that a causal relationship between insurance buying decision and outcomes of moral hazards exists even in the presence of potential confounding variables.

The Rosenbaum bounds analysis relies on the assumption that the probability of an individual insurance buying decision is determined by both observed and unobserved characteristics, written as $\mathrm{P(X, U)}$, where X is the observed characteristics and U are the unobserved characteristics. Assuming $\mathrm{P(X, U)}$ represents the logistic distribution, $\mathrm{P(X, U)} = \exp(\beta \mathrm{X}_i + \alpha \mathrm{U}_i)$. If there is no hidden bias caused by the un-observed characteristics, then $\alpha = 0$ and the probability of buying insurance is determined exclusively by X. On the other hand, if hidden bias presents, then the true probability of buying insurance from two different individuals with same X may be different.

Assuming the odds of individuals i and j buying insurance are $\frac{P_i}{(1-P_i)}$ and $\frac{P_j}{(1-P_j)}$ respectively. The odds ratio is $\frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta X_i + \alpha U_i)}{\exp(\beta X_j + \alpha U_j)}$. In case both individuals' X are identical, the odds ratio can be simplified to $\exp[\alpha(U_i - U_j)]$. And then, the sensitivity analysis measures the impacts on the insurance buying decision when changing the values of α and $(U_i - U_j)$. Assuming U is a a dummy variable and $U_i \in (0, 1)$, the bounds of the equation can be written as, (Rosenbaum, 2002)

$$\frac{1}{e^{\alpha}} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq e^{\alpha}$$

If $e^{\alpha} = 1$, then individuals i and j have the same likelihood of buying insurance. The Rosenbaum bounds analysis will increase the value of e^{α} until the inference on the outcome changes. For example, if $e^{\alpha} = 2$, individuals whose X are similar could differ in their odds of insurance buying decision by as much as a factor of 2. The results are sensitive if values of e^{α} are closed to 1 which could inference that the result is not free of hidden bias.

RESULTS AND DISCUSSION

Based on the observation, we found that households with insurance have significantly different characteristics from those without insurance. Since we consider these differences are signs of selection bias, we applied several methods including the PSM with One-to-one matching with replacement, 5-Nearest neighbours matching, Radius matching and Kernel matching in order to remove the bias. Among these four techniques, the Radius matching method provided the best matching result as shown in Table 3.

Table 3: Comparisons of means of observable variables between the two groups of households based on the Radius matching method

Variable with insurance		Means		t test p>|t|
		without insurance	without insurance	
Age	Before	47.90	44.87	0.03
	After	**47.90**	**48.59**	**0.50**
Education	Before	8.07	8.72	0.02
	After	**8.07**	**7.87**	**0.33**
Expected Loss Ratio	Before	8.00	5.57	0.02
	After	**8.00**	**8.47**	**0.61**
Land rent	Before	4,557.70	3,920.30	0.00
	After	**4,557.70**	**4,534.10**	**0.87**
Non-Farming Income	Before	0.44	0.27	0.00
	After	**0.44**	**0.42**	**0.68**

Using base fertilizer and top-dressing fertilizer are two types of practices in crop management. The base fertilizer is generally a type of compound fertilizer with certain chemical components and applied at the time of seeding by the seeding machine. Meanwhile, the top-dressing fertilizer mainly consists of urea which is applied by labour at the beginning of the jointing stage (Feekes Scale). Based on the PSM, the results indicate that households with crop insurance applied 133.03 kilograms more base fertilizer but 144.49 kilograms less top-dressing per hectare than non-buying households, as provided in Table 4. The behaviour of increasing the use of base fertilizer of households with insurance might cause the crop yields more vulnerable to natural hazards, as Cai et al.,

(2012) demonstrated that under the "base fertilizer only" practice, grain yields were considerably influenced by higher amount of annual rainfall. The authors indicated that as a result of being applied at the time of seeding, the base fertilizer is more likely to be lost by the processes of volatilisation and runoff, leading to lower yields of crops. Even though crop yields may not be different between the two management practices in favourable years, in the case of a bad year, the crop yield harvested from the "base fertilizer only" practice is expected to be much lower than that gained from the method of applying more top-dressing fertilizer at the right stage of the cultivation period.

Table 4: Inputs and Yield results

Outcomes	Means			
	with insurance	without insurance	Difference	
Cost of maize seed (CNY per Ha)	1,065.07	1,026.96	38.11	
Quantity of base fertilizer (KG per Ha)	**595.93**	**466.04**	**129.88**	*
Quantity of top dressing (KG per Ha)	**194.18**	**339.66**	**-145.48**	*
Frequency of herbicide (Time per annum)	**2.64**	**2.34**	**0.30**	*
Frequency of foliar fertilizer (Time per annum)	0.89	0.96	-0.07	
Yield (KG per Ha)	9,241.05	8,865.97	375.08	

* Significant at 95% t-test confidence interval from the Bootstrap with 200 replications

The study also found that households with crop insurance used herbicide more frequently than those without insurance. Most local farmers applied herbicide once at the time of seeding and/or optionally once in the tillering stage with 3 leaves and/or any other time later. In case of good land quality with field management, most farmers only applied the herbicide no more than twice. The lack of field management activities, for example, weeding, from farmers with crop insurance may cause them to apply herbicide more frequently. However, this study found that the cost of maize seed, the frequency of foliar fertilizer and yields are not significantly different between households with and without insurance.

In summary, the study found that the current crop insurance makes households less care about their maize fields. This is considered as a sign of moral hazards in the adoption of new field management practices since households with insurance are more likely to switch from the more yield-effective top dressing to the more yield-uncertain base fertilizer and use more herbicides in caring for their maize crops. Since we conducted the survey during the year with favourable weather conditions and normal level of damages, we cannot find differences in maize yields between the application of the two crop management practices. However, in the case of unfavourable years, we found that yields harvested from maize acreages managed by households with signs of moral hazards associated with crop insurance are expected to be much lower than maize yields gained from the method of applying more top-dressing fertilizer at the right stage of the cultivation period.

What we have done so far, only control the insurance buying decision by the observable characteristics. In order to check for the impact of buying decision by un-observed factors, we follow the sensitivity test by Rosenbaum bounds. Table 5 reports outcome results for both insurance buyers and non-buyers obtained from the Radius matching method. Only outcomes with statistically significant differences between the two groups are tested. The first row illustrates results under the assumption of no hidden bias where $e^{\alpha} = 1$. The significance level on the bound becomes insignificant at the 5% level when $e^{\alpha} = 1.8$, $e^{\alpha} = 2.4$

and e^{α} = 3.6 representing the use of herbicides, base fertilizer and top dressing respectively. The results indicate the level of hidden bias that would the findings insignificant starts in the range from 1.8 to 3.6. This implies that for hidden bias to overturn the statistical significance of the impacts, individuals with the same observed characteristics X should differ in their counterfactuals by a factor of 80 to 260 percent due to unobserved covariates. These are large values since most important variables influencing characteristics of both groups have already been controlled for the observed characteristics. Therefore, these critical values indicate that the results are robust and not sensitive to hidden bias (Diprete & Gangl, 2004). Therefore, we are able to conclude that evidences of the moral hazards in the crop insurance are valid.

Table 5: Rosenbaum Bound Sensitivity Analysis Test for Hidden Biases

e^{α}	P Value		
	Quantity of top dressing	**Quantity of base fertilizer**	**Frequency herbicide usage**
1	0.000	0.000	0.000
1.2	0.000	0.000	0.000
1.4	0.000	0.000	0.002
1.6	0.000	0.000	0.010
1.8	0.000	0.001	**0.032**
2	0.000	0.004	**0.074**
2.2	0.000	0.013	
2.4	0.000	**0.033**	
2.6	0.001	**0.071**	
2.8	0.003		
3	0.007		
3.2	0.015		
3.4	0.027		
3.6	**0.045**		
3.8	**0.070**		

CONCLUSION AND DISCUSSION

The study explores the impacts of crop Insurance in a typical grain growing county in North-east China. Using the data collected from the questionnaire survey for the cultivating season of 2016, some evidence of moral hazards in crop insurance has been discovered in the study.

The study found that crop insurance reduced farmers' concerns about their insured maize areas. Households with insurance used base fertilizers and herbicides more frequently while applying less top-dressing fertilizer, which is considered as signs of moral hazards in crop management, even though the current crop insurance has very high deductible levels as a typical method of controlling moral hazards. In order to further control such moral hazardous behaviour, the insurance's coverage should focus more on outcomes of the risks which are independent of human actions. As Ehrlich and Becker (1972) have argued, the root reason of moral hazard is effects of the insurance on the demand of self-protection, when the state probabilities of outcomes are not independent of human actions. As the pre-defined catastrophic causes are more independent from the farmer's perspective, farmers' behaviour will be less relevant to the insurance buying decision and mitigate the problem of moral hazard. The pre-defined catastrophic causes of losses could be defined as a claimable heavy rain at a higher rainfall level and a claimable drought at a lower rainfall level while increasing the sum of insurance premium per hectare with the same level of the insurance premium.

Based on the information provided by the local insurance company branch, we found that 6,765 farmers out of 8,430 maize insurance policyholders from 2014 to 2016, which equivalents to more than 80 percent of total insurance holders, claimed and received insurance compensation for their losses in maize production. Most of farmers' insurance claims are associated with damages due to heavy rains and severe droughts. The current broad protection that compensates all kinds of natural/biological disasters and accidents may discourage farmers to implement sufficient risk mitigation method to handle minor disasters. While the broad insurance coverage compensates losses from catastrophic disasters, it also compensates damages caused by expected minor disasters where risk mitigation method in good field management can effectively reduce the extent of losses. Due to the fact that most individual households can absorb minor losses by themselves but incapable of handling major damages caused by catastrophic disasters, an appropriate insurance program should pay more attention to compensations for catastrophic loss scenarios rather than compensating 80% of the insurance policyholders.

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Appendices

Appendix I: Expected Insurance Compensation

Each farmer will be asked about the expected chances of 5 payoff cases in the future due to the insured perils as illustrated in Table 6. The farmers' expected insurance compensation of maize is calculated by,

$$Sum\ insured\ \times \sum_{Case}^{3,4,5} (Means\ of\ damaged\ yield_{Case} \times Chance\ of\ happening_{Case})$$

Table 6: Payoff cases and Chances of happening

Payoff case	Damaged yield	Chance of happening	Compensated by the insurance
1	No loss	Implied	No
2	[1%, 30%)		No (Underdeductible)
3	[31%, 50%)		Yes
4	[51%,70%)		Yes
5	[71%,100%]		Yes