Risk and Insurance in Agricultural Economy

Abstract

The negative effects of climate change have begun to exceed expectations and are likely to intensify. This paper studies the effects of the agricultural risk and the insurance on agricultural economy in the context of climate change. First, this paper establishes the model incorporating with the agricultural risk and insurance. The model indicates that the agricultural insurance can effectively reduce the negative impact of risks on agricultural production when the moral hazard has little influence. Next, I verify the hypothesis through the panel data models and the difference-in-difference analysis. The impact of moral hazard in agricultural insurance is very modest. Agricultural insurance can effectively control agricultural risks, especially for the agriculture in the primary industry.

Key Words： Climate Risks，Agricultural Risk，Insurance，Agriculture Economy

JEL Classification: E1, O1, Q1

1. Introduction

At the UN Climate Change Conference on November 29, 2018, the world meteorological organization (WMO) reported that the global warming trend in 2018 was still continuing. Climate change is leading much of the world to experience hotter, longer and more frequent heat waves. The negative effects of climate change have begun to exceed expectations and are likely to intensify as evidence mounts that frequent extreme weather events are linked to climate change. Extreme weather caused by climate change will not only do harm to human health and natural ecosystem, but also bring serious risks to the economy. For example, climate change will significantly increase agricultural risks, causing significant negative impacts on agriculture.

Under the threats of climate risks, people should use relevant risk management tools to control their bad consequences. Agricultural insurance (AI) is one of the most important devices to manage these risks. It can deal with both the risk of price fluctuation and the risk of output decline. Hence, it is a very important tool to stabilize and promote the development of agricultural economy. Theoretically, there are two opposite forces related to AI towards agricultural economy. On the one hand, AI can compensate for the agricultural producers when the loss occur (compensation function). It ensures that agricultural producers can carry out reproduction smoothly. On the other hand, AI may bring about the moral hazard problem. Those who buy AI may cause the increase of the probability or the scale of loss, which is not conducive to the development of agricultural economy. As a result, the effect of AI on agricultural economy depends on the interaction of these two forces. In addition, the promoting effect of AI on agricultural economy can be realized only if the compensation function is achieved. The probability of loss is directly related to the agricultural risk, so for regions with different levels of risks, AI may has different level of promoting effects on agricultural economy. For regions with high agricultural risks, AI may play a more significant role. Based on this, this paper analyzes the impact of climate risk, agricultural risk and AI on agricultural economy.

First, this paper constructs a theoretical model to analyze the impact of the agricultural risk and AI on agricultural economy. Referring to Xu& Liao (2013), this paper builds the risk-insurance RCK model. The contribution of our model is that it take both the compensation function and moral hazard of AI into account. I find that agricultural risk can reduce agricultural output, while AI can release the negative impact of agricultural risk when the moral hazard is modest.

Second, this paper verifies the co-movement of climate risks and agricultural risks. In the past 20 years, the rising of temperature is the major characteristic of climate change. Rising temperatures are contributing to increased drought in many areas, which is destructive for most crop production, as well as affecting livestock, forestry and fisheries. In other words, as the climate warms, the agricultural risk rises. In this paper, the Palmer Drought Severity Index (PDSI) that is commonly used in climatology is treated as the proxy of climate risk.[1] The area hit by disasters (disaster area) and the area where actual loss occurs (loss area) are used as the proxies of agricultural risk. The annual mean of PDSI is significantly negatively correlated with agricultural risk, indicating that the drought-stricken local crops were more seriously affected. The agricultural risk and PDSI fluctuation are positively correlated.

Third, this paper uses fixed effect panel model and dynamic panel model to prove the negative impacts of agricultural risks and the positive effect of AI on the agricultural economy. I obtain a relatively robust conclusion by changing the proxies of agricultural risks and the AI and the econometric methodologies. Also, this paper analyzes the impact of agricultural risk and AI on the four (sub-) industries of the primary industry: agriculture, forestry, animal husbandry and fishery. The AI has the most significant impact on the agriculture and animal husbandry.

In addition, difference-in-difference (DD) method is used to further prove that the AI can promote agricultural economy. AI and agricultural economy may affect each other, which will cause endogeneity problem. Although in the previous analysis, the endogeneity problem is partially solved by using dynamic panel model, more convincing evidences are required. For that reason, based on the fact that China started the policy-

[1] PDSI variables include the annual mean of PDSI in each province (PDSI_A), the longitudinal fluctuation of PDSI (PDSI_Lon) and the lateral fluctuation of PDSI (PDSI_Lat). This paper includes the data of PDSI of each prefecture-level city in each month, while other data are at provincial and annual levels. Thus, I need to calculate the mean and variance of this variable. PDSI longitudinal volatility is the variance of monthly PDSI mean of each province. PDSI horizontal volatility is variance of the PDSI mean of each prefecture-level city per year.

based AI program in 2007 in several pilot provinces, the DD model is constructed. Compared with the non-pilot provinces, the pilot provinces have significantly increased the AI (both premium and payment) after 2007, and their agricultural output have the same change.

Finally, I repeat these exercises for the secondary industry and the tertiary industry to conduct the placebo test. The AI has no significant impact on the output of these two industries. Thus, the possibility of the existence of important variables that affect the output of these three industries at the same time is excluded.

This paper is related to two literatures. First, there are an increasing number of studies on the impact of climate risks on economy (Carleton& Hsiang, 2015). This literature starts from the analysis of agricultural economy. Climate risk has a direct impact on agricultural production. Many studies have found that climate risks can significantly affect the crop production (Lobell& Field, 2007; Lobell et al., 2011; Welch et al., 2010). Existing studies mainly use temperature and precipitation as risk variables. Different from them, this paper selects the more comprehensive PDSI, disaster area and loss area as risk variables. This paper focus on the impact of these agricultural risks on agricultural production, which is an important supplement to the existing literature.

Second, many scholars have studied the effects of risk management on coping with climate risks. One of the most important tools in managing climate risks is AI (Annan& Schlenker, 2015; Schlenker& Michael, 2009). For example, Annan& Schlenker (2015) analyses the AI and climate (including temperature and precipitation) influence on soybean and corn output. They find that extreme temperatures can significantly reduce the output of crops and precipitation and crop yields present an inverted U relationship. They also find that AI further exacerbated the negative effect of climate risk on the production as a result of moral hazard. Different from prior work, our paper further uses policy change to construct DD analysis to solve endogeneity problem more effectively.

The rest of this paper proceeds as follows. In the Section 2, the risk and insurance model is constructed to prove the effect of agricultural risk and AI on agricultural production. The institutional background, data and summary statistics are given in the Section 3. In Section 4, I test the impact of risk and AI on agricultural production. The

DD analysis and placebo test are conducted in Section 5. I conclude in Section 6.

2. Theoretical Analysis

In this section, the theoretical models are constructed to show how the agricultural risk and insurance affect the agriculture. The adverse impact of agricultural risks on agricultural output is easier to explain in theory. Increasing agricultural risk makes the agricultural environment worse, thus reducing agricultural output. Many literatures have discussed this with theoretical models (e.g., Xu &Liao, 2013).

In contrast, the effect of AI on agricultural output is much more complex. First, producers have to pay premiums for purchasing AI, thus occupying a certain share of expenditure and reducing the capital input in agricultural production. After purchasing the AI, due to the existence of asymmetric information, the insured has the incentive to reduce its original risk management investment, thus increasing the possibility of loss (i.e. *Ex-ante Moral Hazard*). In the event of a loss, the AI will provide the insured with corresponding compensation for the loss, thus allowing them to invest more capital into the next phase of production. At the same time, the insured may obtain more insurance compensation by exaggerating the fact of loss or not preventing further loss in time (i.e. *Post-ante Moral Hazard*). Under the combined impacts of premium expenditure (negative), loss compensation (positive) and moral hazard (negative), the comprehensive effect of the AI on agricultural output can hardly be shown intuitively.

In this section, this paper first briefly restates the risk model in the existing literature, and then illustrates the impacts of the AI on agricultural output.

2.1. Risk Model

It is assumed that in an agricultural economy, representative producers can live permanently and have one unit of labor and initial capital. Representative producers maximize their lifetime utility by selecting consumption and savings for each period:

$$U = \sum_{t=1}^{\infty} \beta^t u(c_t)$$

where c_t is the consumption in period t and β is the discount factor of utility. $u(\cdot)$ is the concave utility function with monotone increasing.

The production function is $y = f(k)$. y is the output of the primary industry and k is the capital input which is from the saving of individuals. $f(\cdot)$ is the concave utility function with monotone increasing. Moreover, in order to compare with the risk model, it is assumed that the constant loss ratio in this basic model is EX and it is from 0 to 1. Because the loss is constant, there is no uncertainty or risk. Hence, the budget constraint of the optimal allocation problem is

$$(1-d)k_{t-1} + (1-EX)f(k_{t-1}) = c_t + k_t$$

where d is the depreciation rate of capital. The current consumption and savings (capital input) equal to the depreciated capital in the previous period plus the production after the constant loss. It is well established in the literature that the capital level k^b in the steady state is determined by

$$f'(k^b) = \frac{1-(1-d)\beta}{\beta - \beta EX} \tag{1}$$

Because $f'(\cdot)$ is monotone decreasing, when the constant loss ratio increase, the capital in the steady state will decrease. Hence, the production in the steady state will decrease. However, the constant loss ratio cannot stand for a risky situation as the risk is the loss with uncertainty. Next, this paper will analyze how the agricultural risk influences the production.

The agricultural risk should be incorporated into the model properly. The agricultural risk affects the production environment directly. However, it is very difficult to demonstrate the change of production environment in the RCK model. Agricultural risk ultimately affects agricultural output, so we can make changes in the form of the agricultural output. Referring to Ahsan et al. (1982), the random variable X was used to describe the agricultural risk. The risk loss ratio X is between 0 and 1 and is identical and independent among different periods, i.e. $X_1 = X_2 = \cdots = X$. The expectation of the risk loss ratio is EX. Now the budget constraint becomes:

$$(1-d)k_{t-1} + (1-X)f(k_{t-1}) = c_t + k_t$$

It means that the current consumption and savings (capital input) equal to the capital left over after depreciation in the previous period plus the output after actual loss at the end of the previous period. In the steady state, after introducing the agricultural risk, the capital level k^r is determined by

$$f'(k^r) = \frac{1-(1-d)\beta}{\beta-\beta E[Xu'(c^r)]/E[u'(c^r)]} \tag{2}$$

and the consumption is $c^r = (1-X)f(k^r) - dk^r$. By comparing the equation (1) and (2), we can show how the risk influence the agricultural production. The numerators of these two equations are the same, so we just need compare the constant loss EX and the $E[Xu'(c^r)]/E[u'(c^r)]$.

Proposition 1. *Suppose that (i) the representative producer is under classical RCK model, (ii) the risk loss ratio X is between 0 and 1 and is identical and independent among different periods. Then,*

$$f'(k^r) > f'(k^b)$$

, i.e., the capital and production agricultural economy in the steady state decrease after introducing the uncertainty of loss.

Proof. The risk model is well established in the literature, e.g. Xu and Liao (2013). □

2.2. Risk and Insurance Model

Based on the assumptions and the basic model above, this paper further incorporates the AI to establish the risk-insurance model. Different from models in the literature that only consider the compensation function of the AI, our model supplementally takes the moral hazard into account.

As mentioned above, buying AI needs to pay premium. After purchasing AI, farmers may increase the probability or frequency of crop disaster, so as to increase losses and reduce the agricultural output. In the event of loss, the farmers who apply for AI can get compensation for the loss. Therefore, the budget constraint of the optimization problem becomes:

$$(1-d)k_{t-1} + (1-g(X,\alpha_{t-1}))f(k_{t-1}) + \alpha_{t-1}g(X,\alpha_{t-1})f(k_{t-1})$$
$$= c_t + k_t + \alpha_t(1+\theta)f(k_t)EX$$

where α_t is the insured proportion in period t and its value is from 0 to 1; $\alpha_t = 0$

means no insurance and $\alpha_t = 1$ means full insurance. $g(X, \alpha_{t-1})$ is the loss risk that is influenced by the objective agricultural risk and insured proportion. When the agricultural risk rises, the loss will increase, i.e. $g_X(X, \alpha_{t-1}) \geq 0$. When the insured get higher insurance, they have more or at least the same incentive to behave immorally, thus increasing the loss probability, i.e. $g_a(X, \alpha_{t-1}) \geq 0$. Because of asymmetric information, the insurer cannot price actuarially the moral hazard. Hence, the premium is only based on the expectation of the objective agricultural risks and loading factor (θ). $\theta > 0$ means that the insurance company charges the insured for risk premium and $\theta < 0$ means that the insured get premium subsidy. The current consumption, savings and the AI premium equal to the capital left over after depreciation plus the output after exposure at the end of the previous period and the compensation from the insurance company.

If there is no moral hazard, the loss ratio is only influenced by the objective agricultural risk, i.e. $g(X, \alpha_{t-1}) = \mathrm{X}$. We only need to consider the premium and compensation function of the AI in the budget constraint. In the steady state, the capital level k^r and the insured proportion α are determined by

$$
\begin{aligned}
f'(k^i) &= \frac{1-(1-d)\beta}{\beta-(1+\theta)EX} \\
(1+\theta)EX &= \beta \frac{E[Xu'(c^i)]}{E[u'(c^i)]}
\end{aligned} \tag{3}
$$

and the consumption is $c^i = (1-X)f(k^i) + \alpha X f(k^i) - dk^i - \alpha(1+\theta)f(k^i)EX$. Because $f'(\cdot)$ is monotone decreasing, when the constant loss ratio increase, the capital in the steady state will decrease. When the level of risk premium increases, the cost of the AI is larger and the capital input is less, so the production will decrease. In contrast, when the insured get more subsidy, there will be more capital input, so the production will increase. In the steady state, the fair premium equals to the individual's subjective loss of the uncertainty. The consumption is equivalent to the production after loss exposure and the payment from the insurer minus the depreciated capital and the expenditure of premium.

Finally, I bring the moral hazard into the model. This paper assumes that the effects of the objective agricultural risk are scaled by the moral hazard, i.e. $g_a(X, \alpha_{t-1}) = \mu(\alpha_{t-1})X$. Moreover, there are some evidences in the literature showing that there is little difference in the moral hazard between those who insure 10 percent and those who insure 90 percent of their production. Thus, this paper takes the moral hazard as an exogenous variables. No matter the insurance proportion is, the impact of the moral hazard is the same when the producer has bought the AI, i.e. $g_a(X, \alpha_{t-1}) = \mu X$, $\mu \geq 1, \alpha > 0$. When the agricultural producer has no AI, the situation degenerates into the risk model and the solution is equation (2). Therefore, we only need to consider the situation when the producer has some AI. In the steady state, the capital level k^{im} is determined by

$$\begin{gathered} f'(k^{im}) = \frac{1-(1-d)\beta}{\beta-(1+\theta)\mu EX} \\ (1+\theta)\mu EX = \beta\frac{E[Xu'(c^{im})]}{E[u'(c^{im})]} \end{gathered} \tag{4}$$

and the consumption is determined by $c^{im} = (1-\mu X)f(k^{im}) + \alpha\mu X f(k^{im}) - dk^{im} - \alpha(1+\theta)f(k^{im})EX$. The consumption is equivalent to the production after loss exposure that are magnified by the moral hazard and the payment from the insurer minus the depreciated capital and the expenditure of premium. The risk ratio and the risk premium have negative impacts on the agricultural production. Also, when the effect of moral hazard becomes more significant, the production will decline. If AI can promote agricultural production, then it should satisfy

$$(1+\theta)\mu EX < \beta\frac{E[Xu'(c^r)]}{E[u'(c^r)]}$$

, i.e. the price of AI is lower than the reservation price. The former is the cost of transferring the risk loss and the latter is the individual's subjective loss of the uncertainty. This condition depends on that the influence of moral hazard and the risk premium that cannot be too great. If the impacts of moral hazard are so large that the objective loss surpasses the subjective loss, then the production in the risk and insurance model are lower than the basic risk model.

Proposition 2. *Suppose that (i) the risk loss ratio is determined by the agricultural risk and insured proportion, (ii) the influence of moral hazard is exogenous. Then, when the objective premium is less than the subjective premium,*

$$f'(k^r) > f'(k^{im}) > f'(k^i)$$

, i.e. the AI can promote agricultural production when the moral hazard is modest.

Proof. See Appendix A1. □

2.3. Hypothesis

As the global temperature increases, the climate risk becomes increasingly serious, which brings a lot of negative effects on the economy. The impact on agricultural economy is most significant and direct. As climate risks rise, many areas become drier and less suitable for crops and trees, further affecting livestock and fish. Based on this analysis and the conclusions derived from the risk model, we have the first hypothesis:

Hypothesis 1. *Higher climate risks lead to higher agricultural risks. The higher the agricultural risk is, the lower the agricultural output is.*

In order to test this hypothesis, I first analyze the relationship between climate risks and the agricultural risk through the fixed effect panel data model. The disaster area and the loss area are used as explained variables and the PDSI as explanatory variables. Then, the relationship between the agricultural risk and agricultural output is analyzed by using fixed-effect panel model and dynamic panel model.

Agricultural risk brings tremendous and inevitable impacts on agricultural economy. However, agricultural producers can still mitigate the negative effects of agricultural risks through risk management. This paper focuses on the role of AI in reducing the adverse impact of agricultural risks. As mentioned before, AI has two opposite effects on agricultural economy through the compensation function and moral hazard. The effect of AI on agricultural economy depends on the relative size of these two forces. Based on this analysis and the conclusions derived from the risk-insurance model, we propose the following hypothesis:

Hypothesis 2. *AI can promote agricultural production only when the impact of moral hazard is very small.*

This paper tests the hypothesis by two steps. First, in the section of basic regressions, I use fixed effect model and dynamic panel model to verify that AI can indeed promote agricultural production. Then, in the DD analysis, I further prove the promoting effect of

AI. Meanwhile, I judge the level of moral hazard of AI by analyzing whether there are significant changes of the utilization of fertilizers and pesticides before and after the policy in DD analysis.

In addition, if there is no loss due to agricultural risks in an area, AI is not required to compensate. As a result, AI fails to play the function of compensation and thus fails to play the role of mitigating the negative impact of agricultural risks. In areas where more risks occur, the AI is more likely to show its importance. Therefore, I propose the following hypothesis:

Hypothesis 3. *In regions with higher agricultural risks, AI plays a more significant role in releasing agricultural risks.*

This paper tests this hypothesis by analyzing the coefficient of cross term of agricultural risk and AI. If the coefficient of the cross term is significantly positive, then the hypothesis is correct.

3. Institutional Background and Data

3.1. Institutional Background

The market and total size of AI in China changed dramatically around 2007.Before 2007, the development of AI in China was quite slow. In 1993, the premium income of AI was 377 million yuan. In 2006, the premium income of AI was only 848 million yuan, accounting for only 0.15 percent of the total insurance market. In contrast, the agriculture is very important in China. In 2006, the production of the primary industry accounted for 11.7% of GDP. The AI market does not match the enormous agricultural economy in China.

In 2007, China began to carry out a pilot program of policy-based AI. Inner Mongolia, Jilin, Jiangsu, Hunan, Xinjiang and Sichuan were selected as the pilot provinces for premium subsidies (only for planting industry). The AI premium in 2007 increased to 5.19 billion Yuan; the growth rate was as high as 612.5 percent. After 2007, other provinces began to carry out policy-based AI in succession. The AI premiums per capita of these six selected provinces are shown in Figure 1. There was a jump of AI premium around year 2007. Due to the early implementation of AI in pilot provinces, the development level of AI in these provinces is significantly higher than that of other provinces not only in the year of implementation but also in each subsequent year. As can be seen from Figure 2 (a), the premium or payment person in pilot provinces since 2007 is significantly higher than that in non-pilot provinces.

3.2. Data and Summary Statistics

Two administrative data sets constitute the main source of our empirical analysis. The China Insurance Yearbook provides yearly premium and payment of AI of each provinces. The data of the area hit and affected by disasters, the production of the primary industry and its sub-industries and control variables are from the China Rural Statistical Yearbook. We match these two datasets by the year and the province. In addition, our data for the Palmer Drought Severity Index comes from Dai, Trenberth and Qian (2004).[2] Palmer Drought Severity Index (PDSI) was proposed by Palmer (1995).The index is based on the land's demand and supply of water, taking into account the effects of precipitation and temperature. Generally speaking, high temperature and low precipitation will make the land drier, while low temperature and high precipitation will make the land wetter. PDSI less than -4 indicates severe drought, -3.9 to -3 moderate drought, -2.9 to -2 mild drought, -1.9 to 1.9 normal, and above 1.9 indicates different level of humidity.

The summary statistics are shown in Table 1 and appendix A2. Our data covers the period from 2002 to 2015. Before 2007, the production of the primary industry (logarithmic) of the treatment group and the control group are 16.351 and 15.705 respectively. The average production of treatment group is higher than the control group. After 2007 (including 2007), the average (logarithmic) production of the primary industry of the treatment group and the control group increased to 17.224 and 16.477 respectively. The treatment group shows a more significant increase. Similar changes occurred in the average premiums and payments for AI in these two groups.

[2] The data is available for download at http://www.cgd.ucar.edu/cas/catlog/climmd/pdsi.html.

Prior to 2007, the mean of the PDSI was -1.575, while the PDSI mean for 2007 and subsequent years was -1.245, indicating a drier period prior to 2007. Also, PDSI was more volatile in the period before 2007.[3] Correspondingly, the areas hit or affected by the disaster are larger before 2007 than after 2007.

3.3. Climate Risks and Agricultural Risks

In the past 20 years, the rising of temperature is the major characteristic of climate change. As the climate becomes warmer, the soil becomes drier, agricultural risks rise. Figure 1 illustrates the relationship between the area hit by disasters and PDSI in Hunan province. It can be seen that the trend and change of PDSI and the disaster area are closely related, thus intuitively verifying the close relationship between climate risk and agricultural risk. The figure in appendix A4 shows the similar pattern.

Furthermore, the fixed effect panel data model is used to verify the relationship between climate risk and agricultural risk, and the regression results are summarized in Table 2. It can be shown that the annual average of PDSI is significantly negatively correlated with the disaster area at the level of 5%, and is also negatively correlated with the loss area. This roughly means that the drier the climate is, the higher the agricultural risk is. This result is consistent with the intuitive judgment. In addition, PDSI fluctuations, in both horizontal and vertical level, are significantly positively correlated with the disaster area or the loss area. The greater the PDSI fluctuation is, the greater the dry-wet variation is, the higher the agricultural risk is, and the worse the agricultural output will be.

4. Risk, Insurance and Agriculture

4.1. Baseline Regressions

Next, this paper analyzes the impact of the agricultural risk and AI on agricultural economy. Referring to Annan& Schlenker (2015), the following fixed effect panel data regression is constructed:

[3] In theory, the long-term trend of warming should be towards more drought. However, the results here are the opposite. This is mainly because the period selected in this paper is short. Many studies have shown that the long-term trend for PDSI is indeed to get smaller, that is, to get drier.

$$Y_{i,t} = \beta_1 Risk_{i,t} \cdot Ins_{i,t} + \beta_2 Risk_{i,t} + \beta_3 Ins_{i,t} + \boldsymbol{\gamma X_{i,t}} + \delta_i + \theta_t + \epsilon_{i,t} \qquad (5)$$

This regression controls the region fixed effect and time fixed effect, and is suitable for analyzing the impact of agricultural risk and AI on agricultural output (Hong, Li& Xu, 2019). Regional fixed effect δ_i can absorb the influence of region characteristics that do not change with time. Time fixed effects θ_t can absorb the impact of regional common trend, make the results reflect the agricultural risk and the impact of AI in various regions.

In this regression, $Y_{i,t}$ represents the (log) production of the primary industry. $Risk_{i,t}$ is the agricultural risk. The existing literature has selected agricultural output volatility and the ratio of premium and payment to measure the agricultural risk. However, the major problem in using these proxies for regression analysis is the existence of serious endogeneity problem. In order to release this problem, this paper chooses the ratio of the disaster area or loss area and total cultivated land area to describe the agricultural risk. The higher the ratio is, the higher the agricultural risk is.

In addition, because the improvement of technology may affect the area hit or affected by disaster, also making these two variables endogenous. Hence, this paper further uses PDSI to describe agricultural risk, as the co-movement of PDSI and agricultural risk has been proved in the previous section.

$Ins_{i,t}$ is the premium income or indemnity expenditure of AI in province i in year t. Both premium income and indemnity expenditure can be used to describe the development of AI, but they have strong collinearity, so they should be put into the regression independently. $\boldsymbol{X_{it}}$ is a set of control variables, including the importance of the primary industry (the ratio of production of the primary industry and the GDP), fiscal expenditure related to agriculture, the labor in the primary industry, the fixed assets investment, agricultural machinery power, fertilizers and pesticides. The importance of the primary industry in a province may affect the participation of labor, investment, government support and other aspects of the primary industry. Fiscal expenditure related to the primary industry is one of the most important source of capital in production of primary industry. The labor in the primary sector, the fixed assets investment, agricultural machinery power, fertilizers and pesticides are direct inputs in the production process of the primary industry.

The results of the baseline regression are summarized in Table 3. These regressions all control regional fixed effect, time fixed effect and corresponding control variables. They differ in the choice of proxies of agricultural risk and AI and econometric methodologies. Column (1) takes the proportion of disaster-stricken area as the proxy of agricultural risk and AI premium income as the proxy of insurance. The coefficient of Risk is -0.583 (significant at 1% level), indicating that the increase of agricultural risk will significantly reduce agricultural output. The cross term coefficient of AI and agricultural risk is 0.038 (significant at 1% level), while the coefficient of AI is -0.005 (significant at 5% level). For regions with high agricultural risk, AI can significantly release the negative impact of agricultural risks. For regions with very low agricultural risks, the AI premiums increases the cost of agricultural production, which will inhibit agricultural output. Also, because the loss caused by agricultural risks is very low, the compensate function of AI is not fully reflected. In other words, the effect of AI on agricultural production is not obvious in low risk regions.

Column (2) changes the proxy variable of AI into the indemnity expenditure of AI, and the result is basically consistent with that in column (1). The difference between column (3) and column (1) is that the proxy variable of agricultural risk is changed into the loss area. The result is very similar to that in column (1). As mentioned above, the improvement of agricultural risk management technology may make the loss area endogenous. Therefore, column (4) uses the longitudinal PDSI volatility as the proxy variable of agricultural risk for regression, and the results are consistent with the previous regression.

There was a significant change of AI market in China around 2007. One concern is that the results may be significantly different before and after 2007. Hence, column (5) limits the sample to year 2007 and after and it does not significantly change the results. The results of the first five columns are all based on the baseline regression equation (5). Based on the results of these five columns, we can conclude that the increase of agricultural risks will significantly reduce agricultural output, and AI can effectively release the negative impact of agricultural risks.

4.2. Dynamic Panel Model

However, the regression (5) may have two major problems. First, it fails to control impacts of the last period of agricultural output on the current period of agricultural output. Second, the degree of AI development and agricultural economic development have a two-way causal problem, leading to the endogeneity problem and causing biased regression results. In order to solve these two problems, we further constructs the following dynamic panel model:

$$Y_{i,t} = \alpha Y_{i,t-1} + \beta_1 Risk_{i,t} \cdot Ins_{i,t} + \beta_2 Risk_{i,t} + \beta_3 Ins_{i,t} + \boldsymbol{\gamma Z_{i,t}} + \delta_i + \theta_t + \epsilon_{i,t} \quad (6)$$

In this regression, $Y_{i,t}$ represents the output of the primary industry per capita of i province in year t. $Risk_{i,t}$ is agricultural risk, and the proxy variables used are the same as the basic regression equation. $Ins_{i,t}$ is the premium income or the payment of AI per capita. $\boldsymbol{Z_{i,t}}$ are the control variables, including the importance of the primary industry, financial expenditure related to agriculture, fixed asset investment in the primary industry, total power of agricultural machinery, amount of fertilizer and pesticide. The systematic GMM method is used to estimate this regression and the lag term of AI is used as the instrumental variable.

The last column in Table 3 summarizes the result of the dynamic panel model. Relative to static panel model, it can solve endogeneity problems to some extent. It takes the proportion of disaster area as the proxy of agricultural risk and the premium income as the proxy of AI and clusters at the level of province. The regression results are basically consistent with the results of previous models, indicating the robustness of the conclusion.

4.3. Results of Sub-industries

The primary industry includes agriculture, forestry, animal husbandry and fishery. In China, agricultural insurance is mainly for planting and animal husbandry. We have proved that AI is beneficial to the development of the primary industry on the whole. However, the influence of AI on the four sub-industries may be different. In order to test whether there are differences, the explained variables of regression equation (4) are changed to the output of these four sub-industries respectively. The regression results are summarized in Table 4. For agriculture and animal husbandry, the coefficients of the cross term of risk and insurance are significantly positive at least at the 5% level. However, for forestry and fishery, the regression coefficient of the cross term was not significant. Therefore, the impacts of the AI on these four sub-industries are different. The promoting effect of AI on planting and animal husbandry is more significant.

5. Difference in Difference Analysis and Placebo Test

5.1. Difference in Difference Analysis

Using dynamic panel model can partly solve the endogeneity problem. However, if the influence of the AI on the agricultural economy is over several period, then using lag item as the instrumental variable is not appropriate. In theory, the best solutions to endogeneity problems are random trials and natural trials. For example, Cole et al. (2016) and Mobarak & Rosenzweig (2013) both use the random trials to study the impact of AI on farmers' behavior and agricultural output. However, the cost of random trials is too high and sometimes causes moral and ethical problems, so this paper seeks to find out whether there are natural trials to solve the endogenous problems.

Base on the policy in 2007 that is mentioned in section 3, a proper natural experiment is obtained. It can be intuitively seen from Figure 2 that after 2007, the premium and payment of AI in the treatment group are significantly higher than those in the control group. Furthermore, this paper takes the per capita AI premium and indemnity expenditure as outcome variables respectively to prove the significant difference. After controlling the fixed effect of year and region and other control variables, the event study model is carried out, and the regression coefficient is drawn in Figure 3.[4] It can also be seen that there is a jump of the coefficients around 2007, indicating the difference between the treatment group and the control group. To analyze the effect of AI on production of the primary industry, we establish the following difference in difference (DD) model:

$$Y_{i,t} = \beta_1 Treat_{i,t} \cdot Post_{i,t} + \beta_2 Treat_{i,t} + \beta_3 Post_{i,t} + \boldsymbol{\gamma Z_{i,t}} + \delta_i + \theta_t + \epsilon_{i,t} \tag{7}$$

$Y_{i,t}$ represents the output per capita of province i in year t. $Treat_{i,t}$ is a dummy variable, when its value is equal to 1, it represents the pilot provinces. $Post_{i,t}$ is the policy

[4] For detailed specification for the event study model, please refer to Goodman (2018).

dummy variable whose value is equal to 1 when the year is 2007 and after. What matters here is the sign and significance of β_1. If β_1 is significantly positive, it indicates that AI can promote agricultural production.

In addition, although only six provinces were selected as the pilot in 2007, many other non-pilot provinces also saw an obvious increase in AI premiums in 2007. Therefore, whether a province is a pilot province does not necessarily determine its AI development degree. Hence, in addition to the dummy variable representing whether or not the pilot provinces, I also uses "whether there was a jump increase in AI premiums in 2007" as the grouping dummy. According to the change of AI premium each province around 2007, Beijing, Jilin, Heilongjiang, Hubei, Inner Mongolia, Jiangsu, Hunan, Xinjiang and Sichuan are selected as the treatment group and other provinces as the control group. As can be seen from Figure 2 (b), the per capita premium income of AI in the provinces with obvious jumps since 2007 is significantly higher than that in the non-jump provinces, which can also form a good natural experiment. Based on the above analysis, this paper will make a comprehensive analysis according to the two grouping basis to get a more robust conclusion.

The credibility of the difference-in-difference model depends on two important assumptions. First, the parallel trend hypothesis. The output of the treatment group and the control group have the same trend before and after the policy change. Second, the covariate balance hypothesis. The control variables do not change significantly before and after the policy.

This paper uses graphic method to verify whether agricultural output variables meet the parallel trend hypothesis. Figure 4 (a) shows the per capita output of primary industry in pilot and non-pilot provinces. It can be seen that before 2007, the per capita output of primary industry in pilot is slightly higher than that in non-pilot provinces, but the trend of the two is basically the same. In and after 2007, the difference between the pilot and non-pilot per capita output of the primary industry become more obvious, intuitively indicating that the policy changes in 2007 bring some impact. According to the analysis in previous sections, AI has the most obvious impact on agriculture (planting industry) and animal husbandry. Figure 4 (b) shows the average grain crop yield per acreage of pilot and non-pilot provinces. It can be clearly seen that in 2007 and after, pilot provinces are more than non-pilot provinces. Besides, the parallel trend hypothesis can be proved to be correct intuitively from these figures.

To prove the covariate balance hypothesis, this paper tests whether the individual covariates changed significantly around 2007. Table 5 reports the results of the DD model with individual covariates as outcome variables controlling the fixed effects of time and region. In the regressions with any covariant as the outcome variable, the coefficients of the cross terms are not significant. This suggests that these variables do not change significantly before and after the policy change, hence we verify the assumption of the balance of the covariates.

More importantly, as can be seen from Table 5, there is no significant change in the use of chemical fertilizers and pesticides before and after 2007. The change in the use of chemical fertilizers and pesticides is an important basis for judging the moral risk of AI (Horowitz and Lichtenberg, 1993). Therefore, the influence of moral hazard could be considered as insignificant, verifying one part of the hypothesis.

After testing these two important assumptions: parallel trend and covariate balance, then this paper uses the DD model to analyze the impact of AI on agricultural output. Table 6 summarizes the main results. Column (1) regression takes the production per capita of the primary industry as the outcome variable, and simultaneously controls the fixed time effect and the fixed regional effect. Meanwhile, in order to keep the sample size similar before and after the policy change, the regression of column (1) only selects the samples from 2002 to 2011. The cross term is significantly positive at the level of 5%, indicating that AI can promote agricultural production. However, after the addition of control variables (the results are shown in column (2)), although the cross term is positive, it is no longer significant, which indicates that the positive promoting effect on the output value of the primary industry is not obvious.

As shown above, the impacts of AI on agriculture and animal husbandry in the primary industry is obvious, while the impact on forestry and fishery is not. Therefore, we choose grain crop yield (the most important crop type in agricultural planting) as the outcome variable to strive for more detailed and convincing conclusions. Column (3) in

Table 6 takes the average grain yield per acre as outcome variable and controls time fixed effect, regional fixed effect and other control variables. The sample is limited from year 2002 to 2011. It can be seen that the coefficient of the cross term is significantly positive at the level of 5%, indicating that AI can promote the output of crops. Column (4) extended the sample interval to 2002-2015, and the results were basically consistent with those in column (3). We can conclude that AI can promote agricultural production, but the effect is more obvious for some specific sub-industries.

5.2. Placebo Test

If there were omitted variables that may affect the three industries at the same time, the regression results would be biased. In order to ensure that there are no such problem, we repeat the above baseline regression and DD analysis for the secondary industry and the tertiary industry. The regression results are summarized in Table 7.

Panel A in Table 7 summarizes the results of the baseline regression. Columns (1) and (2) are the results of the secondary industry, both controlling the time and region fixed effect and corresponding control variables. The difference between the two columns is that the second column limits the sample to year 2007 and after. In the case of the whole sample, the regression coefficients of agricultural risk and AI are not significant. Hence, they have no significant influence on the secondary industry. But in the limited sample, the coefficient of agricultural risk is significantly negative at the 5% level and the cross term is also significantly positive. Some industries in the secondary sector that need raw materials from the primary industry are also affected by agriculture-related risks. Columns (3) and (4) are the results of the tertiary industry. No matter in full sample or limited sample, agricultural risk and AI have no significant impact on the tertiary industry. Compared to the primary and secondary industry, the service industry is rarely affected by agricultural risks.

In addition, the DD model is used to analyze the output of the secondary and tertiary industries. The results are shown in Panel B in Table 6. Both time fixed effect and regional fixed effect are controlled and corresponding control variables are added. The coefficients of the cross terms are not significant, indicating that the policy changes in 2007 did not have an impact on the secondary industry. Thus, excluding the existence of variables that affect both the primary industry and the secondary industry. Similarly, the results of columns (3) and (4) show that policy shocks have no significant impact on the output of the tertiary industry. In conclusion, this paper excludes the possibility of the existence of variables that jointly affect the output of these three industries.

6. Conclusion

Through theoretical and empirical analysis, this paper comes to the following conclusions. First, the climate risk and the agricultural risk are closely related. Second, rising climate and agricultural risks reduce agricultural output. Third, moral hazard in AI has little influence. Fourth, AI can effectively deal with the negative impact of agricultural risks on agricultural production.

The research in this paper has important policy significance for individuals, enterprises and governments. First, this paper confirms that individuals and enterprises engaged in agricultural production should deal with agricultural risks through financial instruments such as AI. Second, although moral hazard may occur during the operation of AI, the impact of moral hazard will not prevent AI from playing its role in promoting agricultural production. Therefore, this paper provides theoretical support for the government to continue to develop policy-based AI and insurance companies to continue to operate AI. Third, under the background that the government calls for the mode of "agriculture + insurance + futures", this paper confirms the important role of AI. However, how to play the coordinating role of AI and other financial instruments in promoting agricultural production and guaranteeing farmers' income needs to be further studied.

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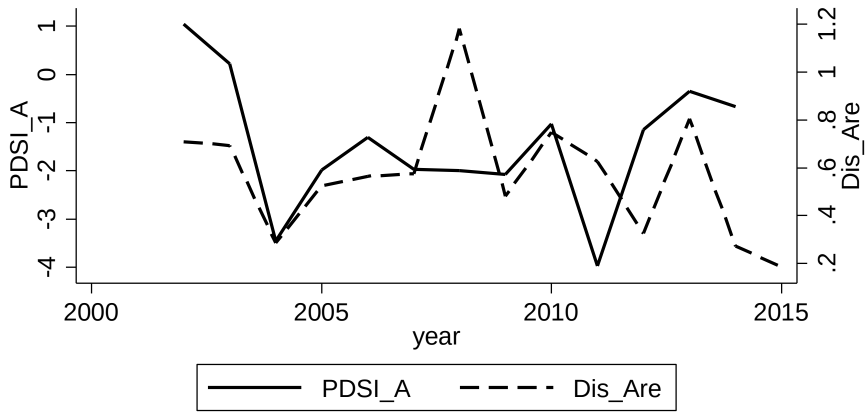
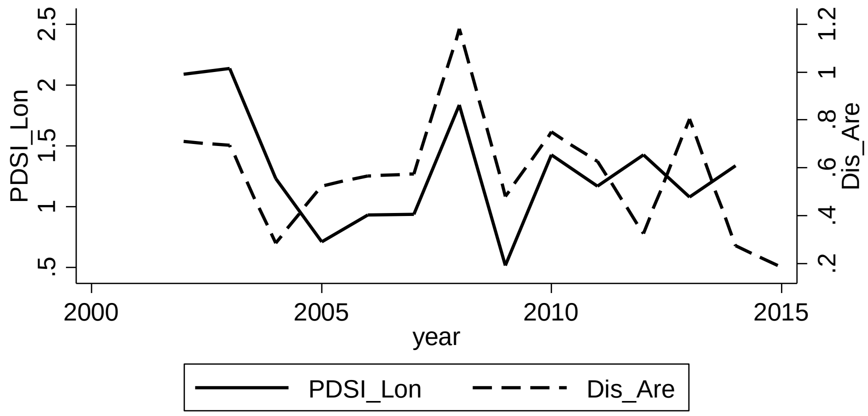
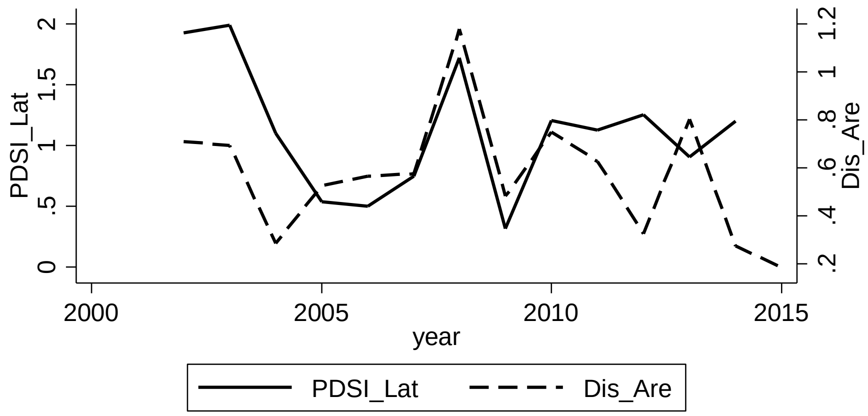
Figure 1. Agricultural Risk and PDSI



(a) Average PDSI and disaster area



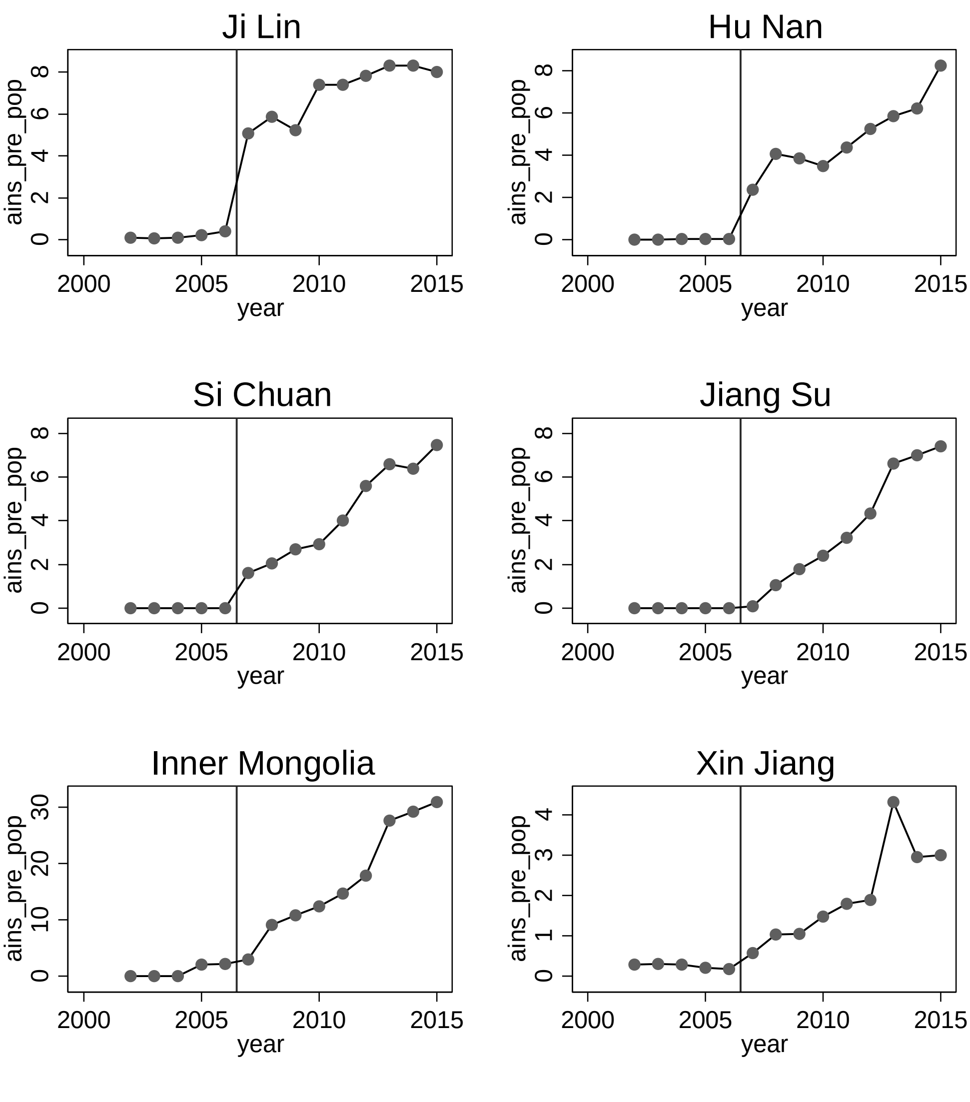
(b) Longitudinal variance of PDSI and disaster area



(c) Lateral variance of PDSI and disaster area

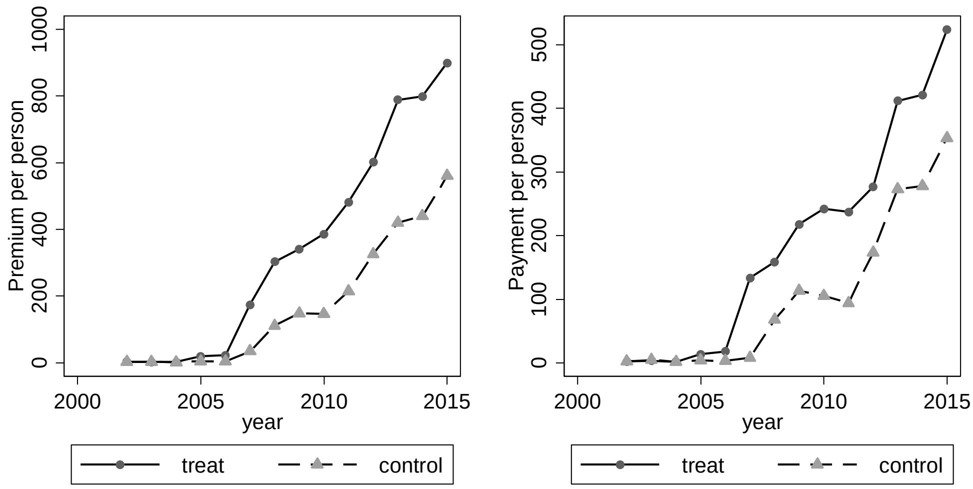
Notes: This figure depicts the co-movement of climate risk and agricultural risk. Proxies of climate risks include average, longitudinal and lateral variances of PDSI. Proxy of agricultural risk is the area hit by disasters. Longitudinal variance is the variance of average PDSI in each month and lateral variance is the variance of average PDSI in each province.

Figure 2. AI Premium of Selected Provinces

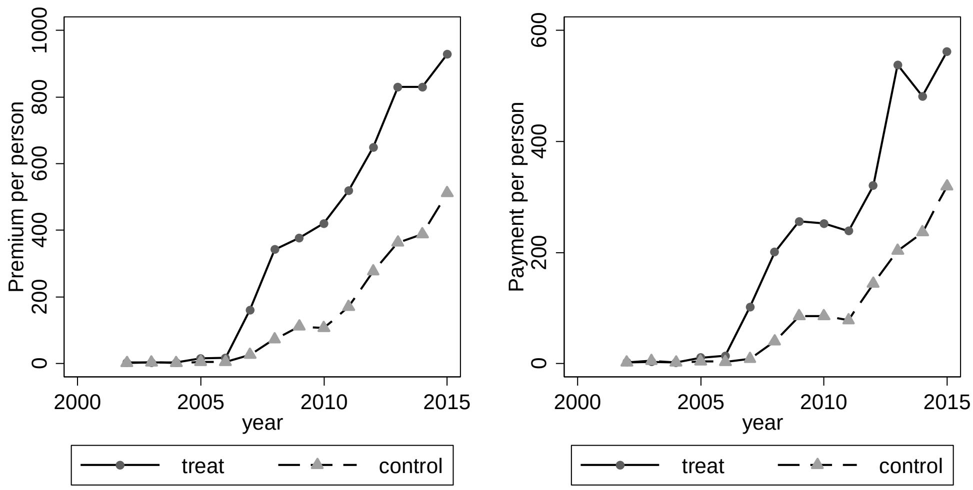


Notes: This figure depicts the agricultural insurance premium per person in selected provinces, including Jilin, Hunan, Sichuan, Jiangsu, Inner Mongolia and Xinjiang. The vertical solid line is at 2006.5, in order to see the change before and after 2007 clearly.

Figure 3 Difference of AI Premium of Treat and Control Groups



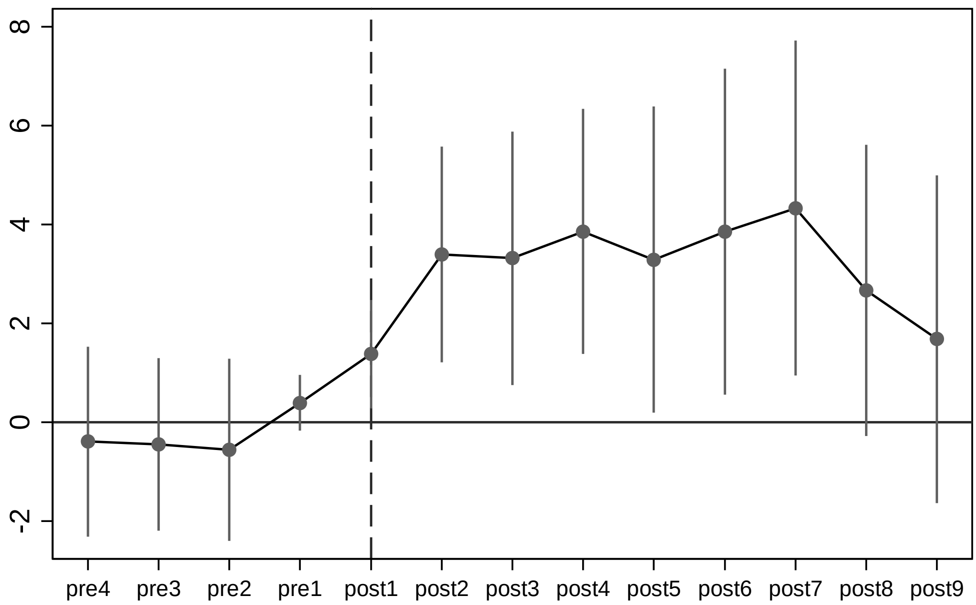
(a) Taking selected provinces as the treatment group



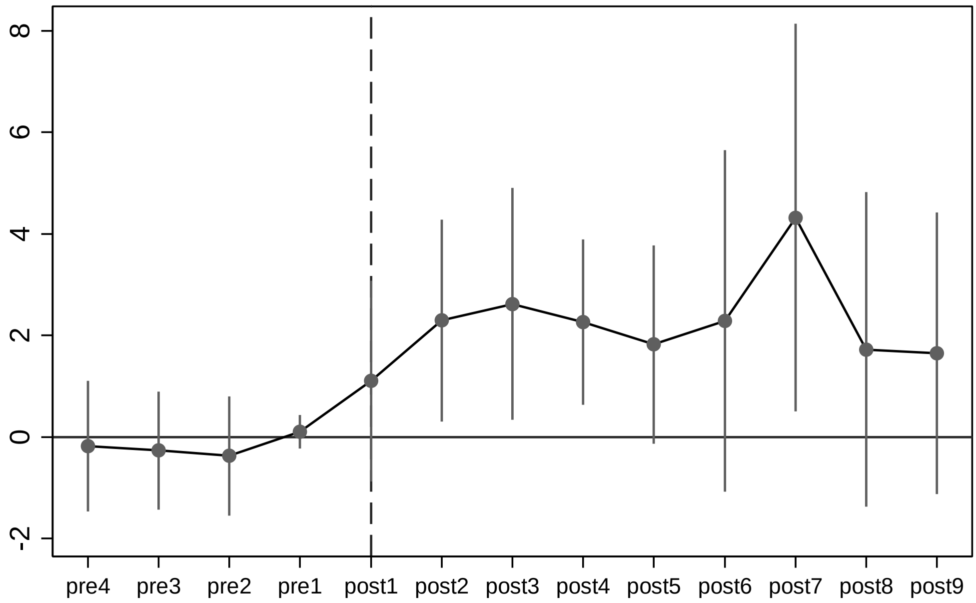
(b) Taking jumping provinces as the treatment group

Notes: This figure depicts the difference of premium or payment per capita of the agricultural insurance of treatment and control groups. Panel (a) takes the selected six provinces as the treatment group and Panel (b) takes these six provinces and other provinces that experience the jump of premium in 2007 as the treatment group.

Figure 4. Coefficient Plots of AI Premium and Payment



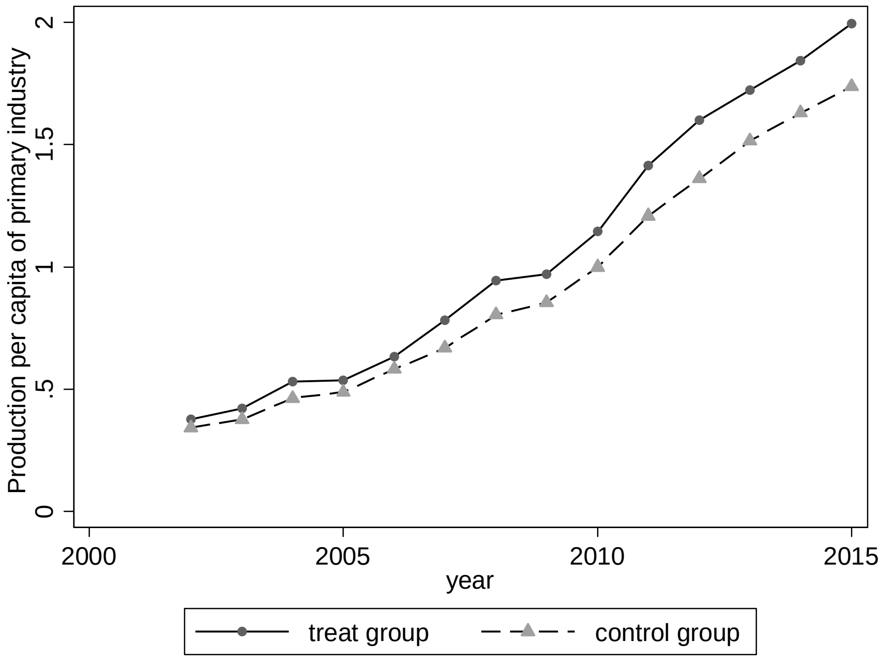
(a) coefficient plot of AI premium



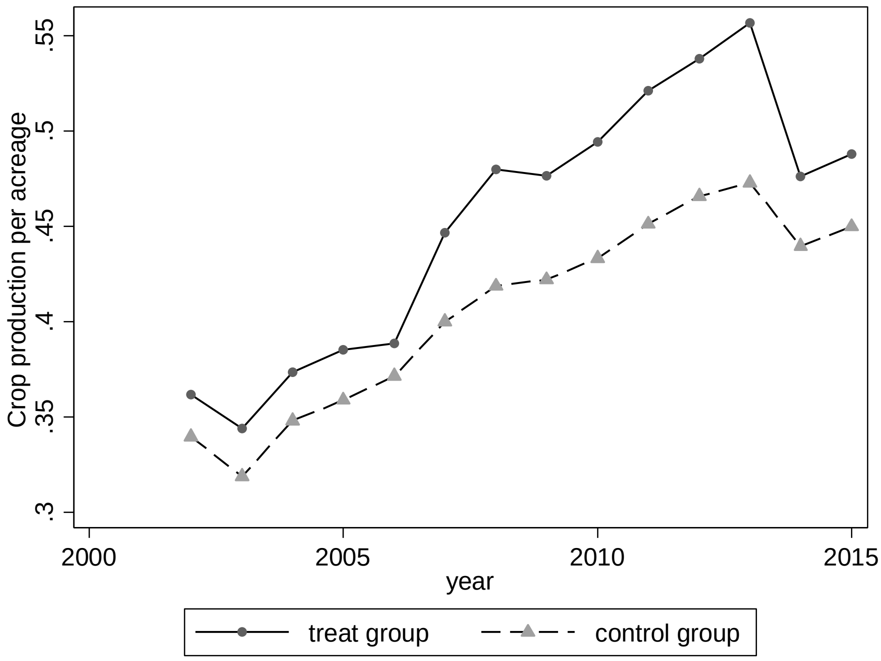
(b) coefficient plot of AI payment

Notes: This figure depicts the coefficients of year t × treated group when the premium or payment of agricultural insurance is the outcome variable. Pre- means the year before 2007 and post- means the year after 2007. The dash line is at the policy year 2007. The solid lines that cross each estimation point of each year is the corresponding confidence interval.

Figure 5. Compare of Production between Treat and Control Groups



(a) Comparison of the Production of the Primary Industry



(b) Comparison of Crop Production per Acreage

Notes: Panel (a) depicts the difference of the output of primary industry per capita between the treatment group and the control group. Panel (b) depicts the difference of the crop production per acreage between the treatment group and the control group.

Table 1. Summary Statistics

Variable	Meaning	Mean	S.D.	Median	P25	P75
Panel A: production (log)						
Pri_Ind	Primary industry	16.339	1.132	16.557	15.517	17.164
Agri	Agriculture	15.672	1.163	15.902	15.023	16.481
Fore	Forestry	13.023	1.280	13.333	12.321	13.886
Husb	Husbandry	15.166	1.097	15.331	14.298	16.085
Fish	Fishery	12.959	2.525	13.287	11.677	14.924
Sec_Ind	Second industry	17.319	1.262	17.488	16.563	18.196
Ter_Ind	Tertiary industry	17.187	1.182	17.321	16.464	17.997
Crop	Crop	16.143	1.218	16.442	15.780	17.114
Panel B: agricultural insurance and risk						
Prem	Premium (log)	15.060	4.118	16.236	13.123	17.932
Paym	Payment (log)	14.474	4.128	15.601	12.901	17.324
Dis_Are	Disaster area	0.291	0.174	0.260	0.174	0.380
Los_Are	Loss area	0.148	0.103	0.128	0.073	0.193
PDSI_A	Average of PDSI	-1.372	1.819	-1.288	-2.565	-0.179
PDSI_Lon	Longitudinal PDSI variance	1.034	0.420	0.971	0.725	1.264
PDSI_Lat	Lateral PDSI variance	0.890	0.433	0.817	0.544	1.154
Panel C: control variables (log)						
Acre	Acreage	17.138	1.066	17.538	16.479	17.864
Fert	Utilization of fertilizer	13.864	1.196	14.133	13.554	14.702
Pest	Utilization of pesticide	19.461	1.380	19.968	18.677	20.549
Fisc	agriculture fiscal expenditure	16.457	0.998	16.504	15.756	17.284
Powe	Agriculture machine power	16.637	1.085	16.821	16.030	17.286
Agr_Pop	Agriculture population	16.538	1.000	16.761	16.225	17.294
Emp_Sec	Employees in second sector	15.176	4.702	16.669	15.805	17.233
Emp_Thi	Employees in third sector	15.394	4.719	16.920	16.222	17.353
Inv_Pri	Investment in primary sector	12.886	1.269	13.150	12.226	13.713
Inv_Sec	Investment in second sector	16.570	1.362	16.641	15.649	17.667
Inv_Thi	Investment in third sector	16.959	1.212	17.107	16.129	17.864

Notes: This table reports summary statistics of all variables. Agricultural population include those employees engaging in primary industry and individual farmers. Disaster area is the area that are affected by agricultural risk and loss area is the area where occurs actual loss. Average PDSI is calculated in province level each year. Longitudinal PDSI variance is the variance of average PDSI in each year, and lateral PDSI variance is the variance of average PDSI in each province. Investment means fixed-asset investment. The sample period is from 1995 to 2014.

Table 2. Climate Risks and Agricultural Risks

	(1)	(2)	(3)	(4)	(5)	(6)
	Dis_Are	Dis_Are	Dis_Are	Los_Are	Los_Are	Los_Are
PDSI_A	-0.015**			-0.006		
	(0.005)			(0.004)		
PDSI_Lon		0.065***			0.045***	
		(0.020)			(0.013)	
PDSI_Lat			0.049***			0.035***
			(0.018)			(0.012)
N	403	403	403	403	403	403
adj. R^2	0.387	0.394	0.388	0.401	0.419	0.412

Notes: This table reports the coefficients of average or variance of PDSI in each column. The first three columns take the area hit by disasters as the explained variable. The last three columns take the area when the loss occurs as the explained variable. All of these six regressions have control the region and time fixed effects. Standard errors, clustered at province level, are included in parentheses. * < 0.10, ** < 0.05, *** < 0.01.

Table 3. Results of Baseline Regressions and Dynamic Panel Model

	(1)	(2)	(3)	(4)	(5)	(6)
Risk× Ins	0.038***	0.026**	0.022***	0.009***	0.062**	0.065**
	(0.007)	(0.008)	(0.002)	(0.003)	(0.019)	(0.028)
Risk	-0.583***	-0.400**	-0.358***	-0.124***	-1.128**	-0.220***
	(0.104)	(0.132)	(0.018)	(0.040)	(0.312)	(0.064)
Ins	-0.005**	-0.004**	-0.006**	-0.011***	0.008	-0.007
	(0.002)	(0.001)	(0.002)	(0.003)	(0.010)	(0.007)
N	424	423	424	395	273	394
adj. R^2	0.996	0.996	0.996	0.996	0.998	
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the coefficients of risk, insurance and their intersection when the (log) production of the primary industry is the explained variable. Column (1) (the basic result) takes the proportion of disaster-stricken area as the proxy of the risk and AI premium as the proxy of the insurance. Column (2) changes the proxy variable of AI into the payment of AI. In column (3), the risk is the area where the actual loss occurs. Column (4) takes the PDSI variance as the risk variable. Column (5) limits the sample to year 2007 and after. The result of the dynamic panel model is summarized in the column (6). All of these six regressions have controlled the region and time fixed effects. The control variables include ecological-economic importance, fiscal agricultural expenditure, the number of first industry labor, the first industry whole social fixed assets investment, agricultural machinery total power, fertilizers and pesticides. Standard errors, clustered at province level, are included in parentheses. $^{*} < 0.10$, $^{**} < 0.05$, $^{***} < 0.01$.

Table 4. Impact of AI on Sub-industries of Agriculture Economy

	(1) Agri	(2) Fore	(3) Fish	(4) Husb
Risk× Ins	0.0246**	0.0216	0.0564***	-0.0090
	(0.0055)	(0.0388)	(0.0104)	(0.0222)
Risk	-0.4653***	-0.1530	-0.8187**	0.4720**
	(0.0716)	(0.6134)	(0.1807)	(0.1348)
Ins	0.0015	-0.0223*	-0.0111*	0.0049
	(0.0009)	(0.0087)	(0.0046)	(0.0046)
N	424	424	424	424
adj. R^2	0.995	0.969	0.992	0.992
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table reports the coefficients of risk, insurance and their intersection when the (log) productions of subsectors in the primary industry are explained variables. All the regressions have controlled the region and time fixed effects and the control variables include ecological-economic importance, fiscal agricultural expenditure, the number of first industry labor, the first industry whole social fixed assets investment, agricultural machinery total power, fertilizers and pesticides. Standard errors, clustered at province level, are included in parentheses. * < 0.10, ** < 0.05, *** < 0.01.

Table 5. Balance Testing of Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pri_GDP	Powe	Fisc	Fert	Pest	Inv_Pri	Los_Are
Time	-6.548***	0.398***	2.998**	0.012***	4.672**	-0.001	-0.032
	(0.754)	(0.043)	(1.165)	(0.002)	(1.828)	(0.003)	(0.024)
Treat	0.587	-0.156	-0.439	-0.004	-1.784	-0.002	0.016
	(2.610)	(0.122)	(0.533)	(0.008)	(3.958)	(0.002)	(0.029)
Treat*Time	0.864	-0.042	0.319	0.002	-1.942	0.005	0.021
	(1.163)	(0.054)	(1.359)	(0.002)	(1.666)	(0.004)	(0.019)
N	434	434	434	434	434	425	433
adj. R^2	0.130	0.162	0.144	0.044	0.003	0.237	0.183

Notes: This table reports the coefficients of difference-in-difference model when covariates are the outcome variable to test the covariates balance hypothesis. All the regressions have controlled the region and time fixed effects. Standard errors, clustered at province level, are included in parentheses. * < 0.10, ** < 0.05, *** < 0.01.

Table 6. Results of Difference in Difference Model

	(1) Pri_Ind	(2) Pri_Ind	(3) Crop	(4) Crop
Treat*Time	0.150**	0.101	0.057**	0.063***
	(0.042)	(0.059)	(0.014)	(0.011)
Time	0.286***	0.059*	-0.011	-0.012
	(0.039)	(0.024)	(0.011)	(0.048)
Treat	0.128	0.001	0.060*	0.060*
	(0.078)	(0.097)	(0.025)	(0.024)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
N	310	305	305	424
adj. R^2	0.503	0.848	0.534	0.510

Notes: This table reports the coefficients in the difference in difference model when the (log) primary industry production or the crop production are the outcome variables. All the regressions have controlled the region and time fixed effects and column (2)-(4) add corresponding control variables. Column (2) has controlled ecological-economic importance, fiscal agricultural expenditure, the number of first industry labor, the first industry whole social fixed assets investment, agricultural machinery total power, fertilizers and pesticides in logarithm. Column (3) and (4) have controlled these variables in per acreage form. Standard errors, clustered at province level, are included in parentheses. * < 0.10, ** < 0.05, *** < 0.01.

Table 7. Placebo Test: Results of Secondary and Tertiary Industries

Panel A				
	(1)	(2)	(3)	(4)
	Sec_Ind	Sec_Ind	Ter_Ind	Ter_Ind
Risk	-0.0226	-0.9784**	-0.1759*	-0.7651
	(0.0942)	(0.4765)	(0.1006)	(0.4976)
Insurance	-0.0016	-0.0011	-0.0038*	-0.0041
	(0.0020)	(0.0087)	(0.0022)	(0.0060)
Risk	0.0020	0.0525*	0.0101	0.0393
*Insurance	(0.0062)	(0.0273)	(0.0067)	(0.0285)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
N	433	278	432	277
adj. R^2	0.997	0.999	0.997	0.999
Panel B				
	(1)	(2)	(3)	(4)
Time	-1.8221***	-1.5312***	-1.4847***	-0.3222***
	(0.3009)	(0.4244)	(0.1424)	(0.0579)
Treat	-0.0394	-0.0638	-0.0177	-0.0366
	(0.0695)	(0.0750)	(0.0714)	(0.0858)
Time*Treat	-0.0267	-0.0045	0.0285	0.0715
	(0.0703)	(0.0750)	(0.0878)	(0.0906)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
N	310	433	310	432
adj. R^2	0.964	0.964	0.963	0.965

Notes: Panel A reports the coefficients of risk, insurance and their cross-term in baseline model and Panel B reports the results of difference in difference model when the (log) secondary industry production or the tertiary industry production is the explained variable. Column (2) and (4) in Panel A limit the sample to the year after 2007. Column (1) and (3) in Panel B limit the sample to the year after 2007. All the regressions have controlled the region and time fixed effects and corresponding control variables. Standard errors, clustered at province level, are include in parentheses. * < 0.10, ** < 0.05, *** < 0.01.