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The role of crop insurance in reducing pesticide use: Evidence from rice farmers in China

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ABSTRACT

Pesticides play a significant role in increasing agricultural yields. However, the overuse of chemical pesticides on crops is a major challenge faced by China, which damages human health, threatens food security, and increases production costs. This paper provides empirical evidence on the relationship between crop insurance and pesticide use. Based on micro-survey data collected from 3410 households, we estimate a control function (CF) approach and find that farmers who purchase crop insurance use 33.30% lower pesticides than those who do not. A series of robustness tests confirm these findings. The results of the moderating effect analysis suggest that rice cultivation training, experience, schooling years, and agricultural laborers can negatively moderate the effect of crop insurance on pesticide use. Furthermore, we also find that the treatment effect of crop insurance is stronger for farmers who are most inclined to purchase crop insurance.

1. Introduction

In China, pesticides are widely used in agriculture production, reducing the crop yield loss caused by pest insects, weeds, and disease (Liu et al., 2015; Zhang et al., 2015a). However, the blind input of pesticides in pursuit of crop yield has been criticized. The increasing studies have alerted the hazards of the excessive pesticide use. On the one hand, the excessive pesticides seriously polluted the ecological environment (Barakat et al., 2013; Jiao et al., 2020; Sah et al., 2020), threatened farmers' health (Aloizou et al., 2020; Berg and Tam, 2018; Lee and Choi, 2020; Zhang et al., 2018), and increased production costs (de O. Gomes et al., 2020; Schreinemachers et al., 2020). On the other hand, pesticide residues have a serious impact on the export of agricultural products (Chen et al., 2015; Drogué and DeMaria, 2012; Li et al., 2018). In 2014, China applied 3.9 times more pesticides than France, 3.8 times more than Germany, 1.25 times more than Japan, and 1.27 times more than South Korea (Zhao et al., 2018). Among food crop production, the largest amount of pesticide inputs were used for rice production in China (Zhang et al., 2015a). As early as 2000, a study pointed out that the actual input of pesticides in rice production was 40% higher than the optimal input under profit maximization conditions (Huang et al., 2000).

Why does the current situation of pesticide use contradict the ideal optimal situation? There are explanations considering both objective reasons and farmers' subjective reasons. First, China has frequent natural disasters, such as floods, droughts, and insect pests. Goluguri et al. (2021) report that brown spot and narrow brown spot are the most common rice diseases, whereas rice production in China faces major challenges due to infestations of rice planthoppers, stem borers, rice blast, and leaf folders (Lou et al., 2014) and could be harmful to crops (Pei et al., 2021). Therefore, farmers often apply pesticides to against natural risks. Second, development economics theory believes that risk aversion is well-known as a general and robust characteristic of smallholders, especially in China, which helps to explain why there are some irrational behaviors of small-scale farmers in agricultural production, such as the overuse of pesticides (Liu, 2013). Data from the National

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Bureau of Statistics showed that up to 2016, there were nearly 260 million rural households in China with an operating scale of fewer than 3.33 ha, accounting for 97% of the total rural households. That is, the vast majority of farmers in China are still engaged in small-scale production (Liu and Huang, 2013), and the risk aversion has inevitably encouraged the increased use of pesticides as one of the measures to prevent risks (Abhilash and Singh, 2009; Gong et al., 2016; Liu and Huang, 2013; Pan et al., 2020). Additionally, most farmers are poorly educated and lack knowledge of agricultural production, leading to irrational pesticide use (Pemsl et al., 2005; Pan et al., 2021). Third, the government has not strictly regulated the use of pesticides in the past (Zhao et al., 2018), and lacks a sound and effective risk defense mechanism (Liu and Huang, 2013). Moreover, the information gap between pesticide retailers and farmers also contributes to the overuse of pesticides (Fan et al., 2015).

In addition to providing training (Zhao et al., 2018), extension services (Wang et al., 2018), and high-quality seeds (Huang et al., 2002), agricultural insurance also appears to mitigate the excessive pesticide use. More than 100 countries have implemented agricultural insurance programs (Mahul and Stutley, 2010). In China, the crop insurance program has achieved great success since the government implemented the subsidy for crop insurance in 2007 (Ke et al., 2015). According to the China Banking and Insurance Regulatory Commission (CBIRC),[1] the national agricultural insurance premium income in 2019 was 67.2 billion yuan, and the guaranteed amount reached 3.81 trillion yuan, covering 70% of the main rice-producing areas. The existing literature provided some evidence that agricultural insurance helps with the reduction in pesticide use. From the perspective of risk preference, using data of cotton farmers from Mississippi in the United States, a study confirmed the moral hazard of cotton insurance, and farmers who purchased insurance would reduce the inputs of herbicides and pesticides (Liang and Coble, 2009). And Chèze et al.(2020) found that farmers are more likely to adopt low-pesticide practices if they believe their income can still be sustained through agricultural insurance after reducing pesticide use. However, some researchers argued that agricultural insurance had a negligible effect on pesticide use (Mishra et al., 2005; Weber et al., 2016). And even some studies showed the opposite result that agricultural insurance could lead to significantly higher expenditures on pesticides (Hill et al., 2019; Möhring et al., 2020a). Overall, it's still unclear whether agricultural insurance would reduce pesticide use. This might be due to studies that ignore pesticide heterogeneity (Möhring et al., 2020b). And it's worth noting that there are some deficiencies in related studies. Existing literature with high relevance to the topic of this paper is based on limited research samples, such as farmers sampled in a state in the United States (Liang and Coble, 2009). Moreover, most existing literature that employs ordinary least squares (OLS) to estimate the effect of agricultural insurance rarely considers that the purchase of agricultural insurance is a self-selection behavior of farmers, which might lead to bias. More importantly, they did not consider that the effects of agricultural insurance could be heterogeneous among farmers with different characteristics and in different regions, failing to provide helpful guides for policy making. Most related literature mainly focuses on the sector of high-value market segments (horticultural or industrial crops), creating an evidence gap in the impact of crop insurance on pesticide use for rice crops that are the most widely cultivated in China. Compared with horticultural or industrial crops, the actual application dosage of pesticides in rice cultivation could cause more potentially severe health hazards and environmental pollution (Qian et al., 2019; Qin and Lü, 2020). As a result, more evidence on the effect of crop insurance on pesticide use in rice cultivation needs to be uncovered.

Given all this, based on a survey of 3410 rice farmers from Chinese rice-producing areas, this paper employs the control function (CF) approach to identify the causal relationship between crop insurance and pesticide use. In addition, several robustness checks, including the endogenous treatment-effects model and the heteroscedasticity-based identification strategy, have confirmed the causal relationship between crop insurance and pesticide use. We find that crop insurance can reduce rice farmers' pesticide use, and the effect of crop insurance is stronger for farmers who have participated in rice cultivation training, with more rice cultivation experience, better education, and more agricultural laborers within the household. Furthermore, we also find that the marginal treatment effects (MTE) are typically stronger than the average treatment effect (ATE) for farmers who are most inclined to purchase crop insurance, which may result from some unobservable individual factors such as the ability to operation or management, and risk preference.

This study makes three contributions to the literature. First, this study provides empirical evidence that crop insurance in China reduces pesticide use among smallholder farmers. Agriculture in southern China is dominated by small-scale operations, making our micro-survey data obtained from 12 major rice-producing provinces in southern China more representative and targeted. Therefore, this study has some reference value for agricultural countries dominated by small-scale production. In addition, this paper focuses on the production of rice, a food crop, filling a research gap in the existing literature on low-value food crops.

Second, this paper considers the heterogeneous effects of crop insurance on pesticide use among farmers with different characteristics in terms of rice cultivation training, experience, schooling years, and agricultural laborers within the household, which helps with deeply understanding the effects of crop insurance and providing a basis for relevant policy making.

Third, this paper effectively addresses the potential endogeneity problem existing in crop insurance that may be attributed to omitted variables and self-selection by introducing the CF approach, endogenous treatment-effects model, and the heteroscedasticity-based identification strategy. Moreover, this paper considers the effect of unobserved factors on the treatment effects of crop insurance and further investigates the MTE for the farmer at the margin of indifference between purchasing or not purchasing crop insurance rather than limiting the ATE.

The remaining part of this paper is portrayed as follows. Section 2 provides the theoretical analysis, and section 3 includes data source and estimation methods. The empirical results are reported and discussed in section 4. Section 5 involves conclusions, policy implications, limitations, and prospects.

2. Theory analysis

Agriculture is inherently risky (Musser and Patrick, 2002). Smallholder farmers in developing countries are often unable to cope with large shocks (Dercon and Christiaensen, 2011). Most farmers are risk-averse, and they see floods, heavy rains, pests, and diseases as threats to agricultural production due to the negative impact of natural disasters on their income (Ullah et al., 2015). Farmers' risk preference plays a vital role in agricultural production decision-making (Liu and Huang, 2013). Compared with risk-neutral farmers, risk-averse farmers are more likely to adopt risk-reducing strategies to stabilize their farming incomes and reduce the uncertainty they face by increasing agrochemical inputs (Di Falco and Perrings, 2005). However, the practice is unsustainable and harmful to environmental protection and human health (Aloizou et al., 2020).

As an effective risk management tool, crop insurance gives an incentive to insured farmers to reduce pesticide use, which is reflected in two aspects. On the one hand, crop insurance can transfer the risks undertaken by farmers. Crop insurance could not only stabilize the income of farmers by contributing to help fight against yield loss due to climate change but also speed up the process of approving loans to

[1] http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=887994&itemId=954&generaltype=0.

insured farmers (Ke et al., 2015) It further enhances the agricultural management abilities and maximizes profits (Budhathoki et al., 2019). That is, crop insurance provides a risk-sharing mechanism for farmers and helps alleviate credit constraints, thereby assisting farmers to escape the poverty trap (Aggarwal, 2010; Alam et al., 2020). In this context, insured farmers have an incentive to reduce pesticide use because they do not need to worry about the risks of yield losses.

On the other hand, crop insurance can promote the adoption of agricultural technologies and pesticide substitutes. Risk aversion and the lack of insurance are major factors that hinder the adoption of modern technologies and pesticide substitutes (Cole et al., 2017; Freudenreich and Musshoff, 2018). Low-income families are more likely to work in traditional agriculture, choosing low-risk technologies and portfolios to avoid permanent damage (Dercon and Christiaensen, 2011). Instead, rich families would adopt modern technologies that risk and profit coexist and benefit from technological innovation (Mosley and Verschoor, 2005). Therefore, crop insurance that reduces risks arising from the use of modern inputs could facilitate technology diffusion (Brick and Visser, 2015). In other words, crop insurance can improve farmers' access to credit and make farmers change their production decisions. For instance, insured farmers are inclined to adopt clean production technologies to substitute pesticides (Farrin and Miranda, 2015; Carter et al., 2016), such as green prevention and control technology and organic production technologies. As a result, the overuse of pesticides would be mitigated. Fig. 1

3. Data and methods

3.1. Data source

The mixed cross-sectional data sets in this paper came from Chinese rice farmers collected between 2018 and 2019, which covered 12 rice-producing provinces in the south of China. Southern China has tropical and subtropical monsoon climates, abundant water resources, and many hills. Food crops are mainly rice, and there are seven major commercial grain bases including Yangtze River Delta, Jianghuai plains, Jianghan Plain, Chengdu Plain, and so on. In the southern region, the degree of scale and mechanization in agricultural production is lower than that in the northern region, and small-scale household-based production forms are universal, which provides a realistic condition for studying small-scale rice farmers. The survey was conducted by distributing questionnaires, and approximately 1,800 farmers were interviewed each year. The questionnaire involved many aspects such as individual characteristics, household characteristics, rice cultivation inputs and outputs, rice processing and marketing.

Survey locations and interviewees were determined by stratified sampling. In 2018, we firstly selected 12 southern rice-producing provinces with a tendency, including Sichuan, Hunan, Guangxi, Fujian, Jiangsu, and so on (see Fig. 2). With the help of provincial agricultural departments, five rice cultivation prefecture-level cities in each province were selected. Second, three townships were selected among these prefecture-level cities. Then, according to the information provided by the agricultural department head of the township, two villages were selected. Finally, based on the list of rice farmers provided by the village committee, five rice cultivation households were randomly targeted in the village as survey respondents. We assigned professionally trained researchers to conduct one-on-one interviews with respondents.

In 2019, we continued to randomly select five rice cultivation households from the same villages sampled last year and conducted the same investigation. From 2018 to 2019, we collected a total of 3,518 questionnaires, and the valid questionnaires were 3,410 after eliminating the samples with serious missing or abnormal information.

3.2. Selection and definition of variables

(1) Pesticide use

Inspired by Zhang et al. (2015b), Schreinemachers et al. (2020), and Möhring et al. (2020b), this paper chooses the average pesticide use per ha to measure the pesticide use. In China, more than 50% of the excessive pesticide use cases in rice cultivation occurred in the control of pests and diseases such as rice striped stem borer, planthopper, leaf folder, thrip, and sheath blight. And Rice farmers usually apply abamectin, bisultap, chlorpyrifos, Jingangmycin, paraquat, and imidacloprid to manage crop pests and diseases (Zhang et al., 2015b). Thus, the impact of pesticide heterogeneity on the empirical results of this paper is minimal.

(2) Crop insurance

The range of crop insurance in this paper mainly involves natural disasters such as pests, diseases, floods, high temperatures, and hail. China has been initiated subsidized crop insurance programs (CIPs) since 2007. The policy-supported crop insurance is subsidized by the national, provincial, and municipal financial departments respectively. In general, farmers spend only 20% of the expense on crop insurance (Lyu and Barré, 2017). Insurance in this paper is a dummy variable, 1 if the household purchases crop insurance, and 0 otherwise.

(3) Individual and household characteristics

Following Sharma et al. (2015), Khan et al. (2015), Fan et al. (2015), Schreinemachers et al. (2017), Zhang et al. (2018), and Wang et al. (2018), this study controls two sets of characteristics. The individual set includes household heads' gender, age, schooling years, health, cultivation experience, training, and risk perception. The household set involves household assets per capita, family size, agricultural laborers within the household, cooperative membership, and rice area. Table I in the appendix shows all variable definitions.

(4) Provincial and year fixed effects

To address the impact of unobserved confounding factors on empirical results, this paper also includes provincial and year fixed effects. Provincial variables can control differences in pesticide use among regions, which are due to different insurance policies and geographical locations. And year variables are used to control the influence of

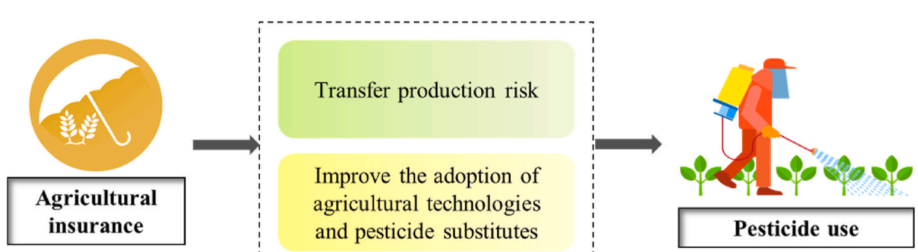

Fig. 1. The theory analysis.

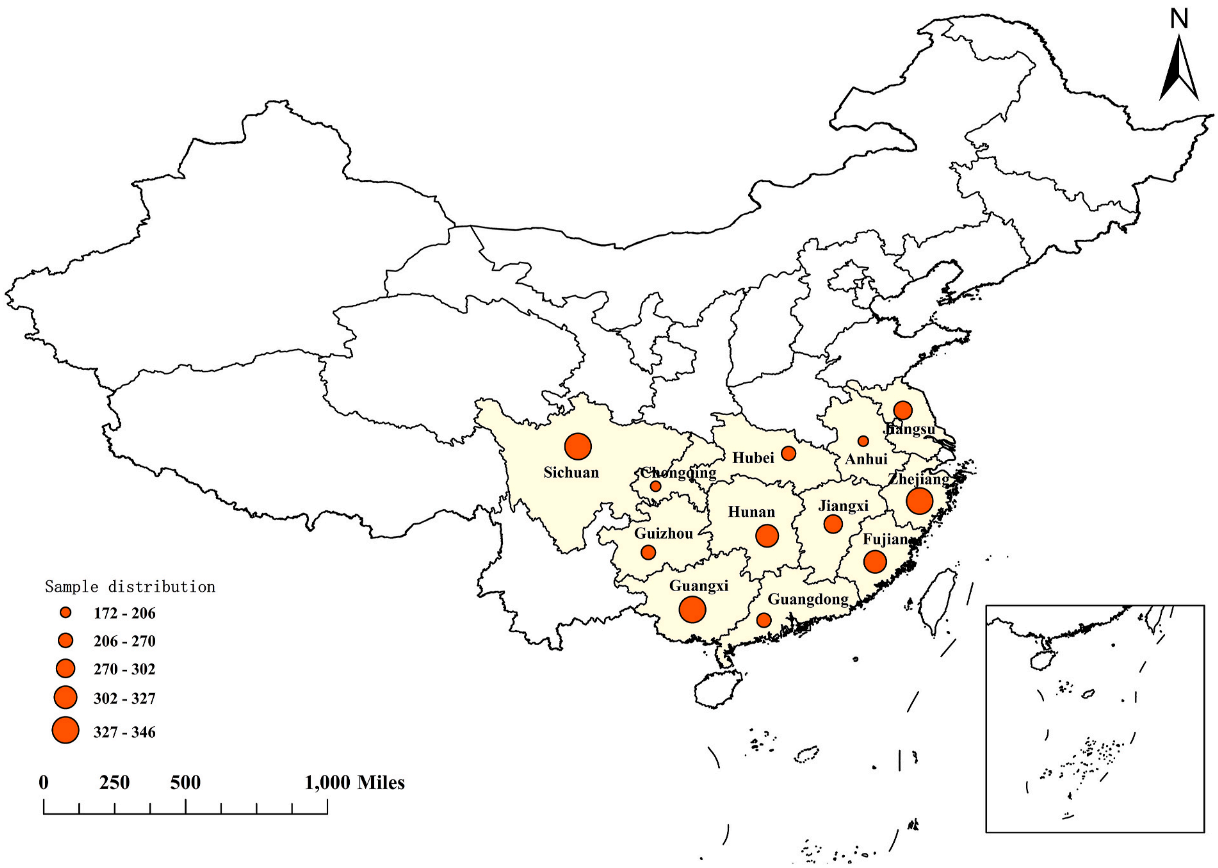

Fig. 2. The distribution of selected rice production areas in China.

macroeconomic fluctuation.

3.3. Conceptual framework

In this section, using a farmer's production model based on the model created by Horowitz and Lichtenberg (1993), we present a framework to explain how households' decision to purchase crop insurance influences their pesticide use.

First, we assume that the rice production function can be defined as $O = f(y, n)$, where O denotes output, y denotes production input (including pesticides), and n represents a vector of random state of the natural environment. The value of n is $\{1, 2\}$, $n = 1$ and $n = 2$ indicate that the farmers carry out rice production under the condition of no disaster risk and the condition of disaster occurrence, respectively. The probability of disaster occurrence is set as θ, and the price of rice per unit is p, the price per unit of the production input is. ω.

Secondly, we further define risk-increasing production inputs and risk-reducing production inputs. Usually, we default that $\frac{\partial f(y,1)}{\partial y} > 0$. If $\frac{\partial f(y,1)}{\partial y} \le \frac{\partial f(y,2)}{\partial y}$, then the input makes the marginal product under risk-free conditions smaller than that under-disaster conditions, then it can be defined as a risk-reducing input. If $\frac{\partial f(y,1)}{\partial y} > \frac{\partial f(y,2)}{\partial y} \ge 0$, this input can be defined as a weak risk-increasing input, and if $\frac{\partial f(y,1)}{\partial y} > \frac{\partial f(y,2)}{\partial y}$, where $\frac{\partial f(y,2)}{\partial y} < 0$, then we can assert that this input is a strong risk-increasing input. Notably, pesticides are commonly considered as a risk-reducing input (Smith and Goodwin, 1996). When pests and diseases occur, the average yield of plots with pesticides is significantly higher than that without pesticides, which is also proven by many natural science experiments (Mishra et al., 2005).

Finally, based on the principle of maximizing the expected utility of farmers, we analyze the production behaviors of insured and non-insured farmers. For non-insured farmers, the expected utility function $EU(\pi)$ is expressed as:

$$EU(\pi) = (1-\theta)U[pf(y,1) - \omega y] + \theta U[pf(y,2) - \omega y] \tag{1}$$

Then we calculate the first-order partial derivative of y in equation (1) to obtain the marginal expected utility function of non-insured farmers, which could be organized as:

$$\begin{aligned}\frac{\partial EU(\pi)}{\partial y} &= (1-\theta)U'[pf(y,1) - \omega y]\left[p\frac{\partial f(y,1)}{\partial y} - \omega\right] \\ &+\theta U'[pf(y,2) - \omega y]\left[p\frac{f(y,2)}{\partial y} - \omega\right]\end{aligned} \tag{2}$$

$\frac{\partial EU(\pi)}{\partial y} = 0$ when maximizing the expected utility of non-insured farmers.

For insured farmers, the insurance premium is C. When the rice output of farmers is $O^* \ge O$, where O^* is the critical indemnity output and γ is the indemnity rate ($\gamma > 0$), the indemnity amount that the farmer can get is $\gamma(O^* - O)$. The expected utility function of rice production of the insured households is expressed as:

$$EU(\pi^*) = (1-\theta)U[pf(y,1) - \omega y - C] + \theta U[pf(y,2) - \omega y + \gamma(O^* - O) - C] \tag{3}$$

Similar to equation (2), the marginal expected utility function of insured farmers is calculated as follows ($\frac{\partial EU(\pi^*)}{\partial y} = 0$ when maximizing the expected utility of insured farmers):

$$\begin{aligned}\frac{\partial EU(\pi^*)}{\partial y} &= (1-\theta)U'[pf(y,1) - \omega y - C]\left[p\frac{\partial f(y,1)}{\partial y} - \omega\right] \\ &+\theta U'[pf(y,2) - \omega y + \gamma(O^* - O) - C]\left[p\frac{f(y,2)}{\partial y} - \gamma\frac{\partial f(y,2)}{\partial y} - \omega\right]\end{aligned} \tag{4}$$

Given the above, if a farmland input is strong risk-increasing, $\frac{\partial EU(\pi^*)}{\partial y} > \frac{\partial EU(\pi)}{\partial y}$. For weak risk-increasing and risk-reducing input, such as pesticides, $\frac{\partial EU(\pi^*)}{\partial y} \leq \frac{\partial EU(\pi)}{\partial y}$.

In conclusion, farmers who purchase crop insurance will tend to increase the strong risk-increasing input and reduce the input of other types such as pesticides.

3.4. Methods

3.4.1. Control function approach

The above discussion shows that farmers are assumed to choose crop insurance to maximize their expected utility. To identify the effect of crop insurance on pesticide use, we estimate the following set of regressions:

$$D_i^* = \alpha_1 Z_i + \alpha_2 X_i + \rho,\ D_i = \begin{cases} 1, if\ D_i^* \geq 0 \\ 0, otherwise \end{cases} \tag{6}$$

$$y_i = \beta_1 D_i + \beta_2 X_i + \varepsilon \tag{7}$$

where y_i represents the pesticide use, D_i is the purchase decision of crop insurance, and X_i is a vector of control variables that affect y_i and D_i. α_1 and α_2, β_1 and β_2 are vectors of parameters to be estimated. ρ and ε are random error terms. Notably, there must be at least one valid instrument, Z_i, which should directly affect farmers' decisions about the purchase of crop insurance but has no direct effect on pesticide use. In the empirical estimation, we employed two instrumental variables. One is the proportion of crop insurance purchases in the village where the household is located, and the other one is the distance from the household to the village committee. Because peer effects and the distance could not directly affect pesticide use by farmers, but they would influence households' decisions and behaviors (Lyu and Barré, 2017; Zeng et al., 2019). The ordinary least squares (OLS) is generally applied to estimate parameters since y_i is a continuous dependent variable. However, in a realistic situation, the crop insurance purchase is potentially endogenous, caused by omitted variables, selection bias, and measurement error. It would result in a correlation between ρ and ε, leading to inconsistency when applying OLS to Equation (7).

We controlled endogeneity bias by a two-stage CF approach (Rivers and Vuong, 1988; Wooldridge, 2015). In the first stage, it requires us to obtain predicted generalized residuals from a regression model in equation (6), which could be expressed as:

$$R = D_i \lambda(\alpha_1 Z_i + \alpha_2 X_i) - (1 - D_i)\lambda(-\alpha_1 Z_i - \alpha_2 X_i) \tag{8}$$

where λ is the inverse Mills ratio. In the second stage of the CF approach, the obtained generalized residual is introduced as an additional covariate to equation (7), and then the model is rewritten as:

$$y_i = \beta_1 D_i + \beta_2 X_i + \beta_3 R + \varepsilon \tag{9}$$

In line with Vella (1998), the regression model of pesticide use includes a generalized residual that provides a consistent estimate. However, a statistically insignificant residual in equation (9) would reveal that the endogenous explanatory variables have been consistently estimated (Wooldridge, 2015).

3.4.2. Heteroscedasticity-based identification strategy

This study also implements the heteroscedasticity-based identification strategy to examine the bias caused by endogeneity problems. Lewbel (2018) had put forward instruments based on the product of the selected demeaned regression variables and the first-stage regression residuals. Under reasonable assumptions, these instruments meet the exclusion restriction because they are not related to other regression variables. If there is heteroskedasticity in the first stage, the relevant conditions are met, and the test can be conducted. Essentially, heteroscedasticity helps predict endogenous regression. In specific, equation (7) is also used here.

Following Lewbel (2018), equation (10) is estimated as follows:

$$D_i = \eta S_i + \omega \tag{10}$$

where S_i is a vector of internal instruments, which can be either the same as X_i or a subset to it. The residual ω is then used to generate higher-moment instruments $(S_i - \overline{S_i})\widehat{\omega}$, in which $\overline{S_i}$ is the mean of S_i, and $\widehat{\omega}$ is the estimated residual of equation (10).

Lewbel (2018) proposed that in the case of three conditions, β_1 in equation (7) can be consistently estimated without exclusion restrictions. First, $E(X_i \varepsilon) = 0$ and $E(S_i \omega) = 0$, meaning that all variables in X_i should be exogenous for y_i, and all the variables in S_i should be exogenous for D_i. Second, $Cov(S_i,\ \varepsilon\omega) = 0$, which implies that S_i is uncorrelated with ε and ω. Third, $Cov(S_i, \omega^2) = 0$, requiring the existence of heteroscedasticity in equation (10).

3.4.3. Endogenous treatment-effects model

In this paper, the endogenous treatment-effects model is introduced to estimate the effect of crop insurance on pesticide use as well. Given the primary models as follows:

$$y_{i0} = E(y_{i0}|x_i) + \varepsilon_{i0} \tag{11}$$

$$y_{i1} = E(y_{i1}|x_i) + \varepsilon_{i1} \tag{12}$$

$$t_i = E(t_i|R_i) + v_i \tag{13}$$

$$y_i = t_i y_{i1} + (1 - t_i) y_{i0} \tag{14}$$

$$E(\varepsilon_{ij}|x_i, R_i) = E(\varepsilon_{ij}|R_i) = E(\varepsilon_{ij}|x_i) = 0\ for\ j \in \{0, 1\} \tag{15}$$

$$E(\varepsilon_{ij}|t) \neq 0\ for\ j \in \{0, 1\} \tag{16}$$

where y_{i0} is pesticide use of the household i without crop insurance, and y_{i1} is pesticide use of the household i with crop insurance; t_i is the observed binary treatment, which presents whether the household purchased crop insurance; y_i is the observed outcome; ε_{ij} and v_i are unobserved components. The expected value that conditional on both a set of regressors x_i and an unobserved random component ε_{ij} determined every potential outcome, for $j \in \{0, 1\}$. Equations (13), (15) and (16) are the basis of the control-function estimator. And equation (15) states that there is no correlation between the unobserved components in the potential outcome and R_i. Equation (16) involves endogeneity in the framework, indicating that the unobserved components in the potential outcome equations are correlated to treatment status. Thus, the correlation between t_i and unobserved components must be consistent with that between ε_{ij} and v_i. From equations (13) and (15), $E(\varepsilon_{ij}|t_i)$ can be denoted as:

$$E(\varepsilon_{ij}|t_i) = E(\varepsilon_{ij}|E(t|R_i) + v_i) = E(\varepsilon_{ij}|v_i) = v_i \delta_{2j} \tag{17}$$

Then, $\widehat{v_i}$, the difference between the t_i and $E(t_i|R_i)$, is obtained by probit estimator, and the $E(y_{ij}|x_i, v_i, t_i)$ can be calculated. If the outcome is linear, equations are as follows:

$$E(y_{ij}|x_i, v_i, t_i = j) = x_i^{'} \delta_{1j} + v_i \delta_{2j}\ ,\ j \in \{0, 1\} \tag{18}$$

$$E(y_{ij}|x_i, v_i, t_i = j) = \Phi(x_i^{'} \delta_{1j} + v_i \delta_{2j}) \tag{19}$$

Using the generalized method of moments (GMM), the average treatment effect (ATE) and the potential-outcome means (POMs) are estimated. The moment conditions in the GMM estimation for the linear model are given by:

$$\frac{1}{n}\sum_{i=1}^{n} x_i'\left(y_i - x_i'\widehat{\delta_{1j}} + \widehat{v_i}\widehat{\delta_{2j}}\right)t_i = 0 \tag{20}$$

$$\frac{1}{n}\sum_{i=1}^{n} x_i'\left(y_i - x_i'\widehat{\delta_{1j}} + \widehat{v_i}\widehat{\delta_{2j}}\right)(1-t_i) = 0 \tag{21}$$

$$\frac{1}{n}\sum_{i=1}^{n} R_i'\left\{t_i\frac{\varphi(R_i'\widehat{\tau})}{\Phi(R_i'\widehat{\tau})} - (1-t_i)\frac{\varphi(R_i'\widehat{\tau})}{1-\Phi(R_i'\widehat{\tau})}\right\} = 0 \tag{22}$$

$$\frac{1}{n}\sum_{i=1}^{n}\left\{\left(x_i'\widehat{\delta_{10}} + \widehat{v_i}\widehat{\delta_{20}}\right) - \widehat{POM0}\right\} = 0 \tag{23}$$

$$\frac{1}{n}\sum_{i=1}^{n}\left\{\left(x_i'\widehat{\delta_{11}} + \widehat{v_i}\widehat{\delta_{21}}\right) - \widehat{POM0} - \widehat{ATE}\right\} = 0 \tag{24}$$

Where $\widehat{v_i} = t_i - \Phi(R_i'\widehat{\tau})$, n is the number of observations, and $\widehat{\delta}$, $\widehat{\delta_{11}}$, $\widehat{\delta_{20}}$, $\widehat{\delta_{21}}$, $\widehat{\tau}$, $\widehat{\text{ATE}}$ and $\widehat{POM}0$ are parameters. Therefore, the POMs are estimated by replacing equation (24):

$$\frac{1}{n}\sum_{i=1}^{n}\left\{\left(x_i'\widehat{\delta_{11}} + \widehat{v_i}\widehat{\delta_{21}}\right) - \widehat{POM1}\right\} = 0 \tag{25}$$

where $\widehat{POM}1$ is a parameter of the model.

3.4.4. Marginal treatment effects

The above empirical approaches estimate the purchase decisions of crop insurance by farmers based on observable characteristics. In other words, these methods assume that survey objects are homogeneous, neglecting the impact of unobservable characteristics on farmers' decisions. As a matter of fact, farmers who have the same observable characteristics may make different decisions owing to the unobservable heterogeneity such as individual ability, attitudes, and expectations. Hence, studying the average treatment effects of the marginal farmers who are at the margin of indifference between buying or not buying crop insurance can make the estimates more accurate. According to Heckman and Vytlacil (2007), the MTE depends on the individual characteristics X and the unobserved utility U_D:

$$MTE(x, u_D) = E(Y_1 - Y_0 | X = x,\ U_D = u_D) \tag{26}$$

where U_D is related to the propensity to purchase crop insurance. Then the expectation of pesticide use in equation (14) can be written as:

$$\begin{aligned} E(Y|X=x,\ P(Z)=p) &= E(tY_1 + (1-t)Y_0 | X=x,\ P(Z)=p) \\ &= E(Y_0 + (Y_1 - Y_0)t | X=x,\ P(Z)=p) \\ &= E(Y_0|X=x) + E(Y_1 - Y_0|X=x,\ t=1)\Pr(D=1|Z=z) \\ &= E(Y_0|X=x) + \int_0^p E(Y_1 - Y_0|X=x,\ U_D=u_D)du_D \end{aligned} \tag{27}$$

Thus, the MTE in equation (26) can be represented by the partial derivative of this expression with respect to p evaluated at $p = u_D$:

$$MET(x, p) = \frac{\partial E[Y|X=x,\ P(Z)=p]}{\partial p}\Big|_{p=u_D} \tag{28}$$

4. Results

4.1. Descriptive analysis

Table 1 presents the sample statistics and the useful background in this study. About 70% of the surveyed households have purchased crop insurance, and the average pesticide use is 20.88 kg per ha. In addition, most household heads were male, with about 8 years of formal education, and middle or old age. Household heads, on average, have been cultivating rice for 26.8 years, and more than 80% of them had participated in rice cultivation training. Moreover, 44.8% of households had perceived risks from rice pests and diseases. The mean household assets per capita were approximately 35 thousand yuan. A household had about 4 persons and with 2 agricultural laborers. The mean rice area per household was 3.54 mu, and 23% of households joined a cooperative.

Table 1
Sample statistics.

Variables	Observations	Mean	Std. Dev.	Min	Max
Pesticide use	3,410	20.88	26.04	0	450
Ln (pesticide use)	3,410	2.676	0.934	0	6.111
Insurance	3,410	0.703	0.457	0	1
Insurance proportion	3,410	0.703	0.326	0	1
Distance	3,410	11.28	5.761	0	22
Gender	3,410	0.918	0.275	0	1
Age	3,410	51.95	7.536	21	65
Schooling	3,410	8.169	2.616	0	17
Health	3,410	2.402	0.533	1	3
Experience	3,410	26.80	10.24	1	49
Training	3,410	0.802	0.399	0	1
Risk perception	3,410	0.448	0.497	0	1
Assets	3,410	35,435	51,429	900	609,750
Ln (assets)	3,410	10.07	0.818	6.802	13.32
Family size	3,410	4.589	1.612	1	15
Agricultural laborers	3,410	2.049	0.790	0	7
Membership	3,410	0.230	0.421	0	1
Rice area	3,410	3.537	15.97	0.0133	311.7
Ln (rice area)	3,410	−0.573	1.487	−4.317	5.742

Table 2 reports the mean differences between the control group and the treatment group. This simple test provides evidence that compared with farmers who did not purchase crop insurance, farmers who purchased crop insurance used fewer pesticides. However, considering that the purchase of crop insurance might be a self-selection behavior of farmers (Aditya et al., 2018), our exception needs to be further explored in the following sections. In addition, farmers who purchased crop insurance had better education, less cultivation experience, more household assets per capita, and larger rice cultivation area. Meanwhile, their houses are close to the village committee, and they had joined a cooperative.

Fig. 3(a) and (b) describe the average pesticide use per ha and the crop insurance coverage rates in different provinces, respectively. Some provinces with a higher crop insurance coverage rate apply fewer

Table 2
The mean differences between the control group and treatment group.

Variables	Control group (without insurance)		Treatment group (with insurance)		Difference	
	Mean	S.D	Mean	S.D	Mean	p-value
Ln (pesticide use)	2.752	0.819	2.643	0.977	−0.109	0.002
Distance	13.335	7.529	10.417	4.553	−2.918	0.000
Gender	0.907	0.290	0.922	0.268	0.015	0.143
Age	51.680	7.605	52.064	7.505	0.383	0.175
Schooling	7.792	2.682	8.329	2.572	0.537	0.000
Health	2.402	0.548	2.402	0.527	0.000	0.982
Experience	27.626	9.756	26.452	10.416	−1.174	0.002
Training	0.735	0.442	0.830	0.376	0.095	0.000
Risk perception	0.431	0.495	0.455	0.498	0.024	0.199
Ln (assets)	9.857	0.779	10.164	0.817	0.307	0.000
Family size	4.576	1.654	4.595	1.595	0.019	0.756
Agricultural laborers	2.056	0.757	2.045	0.803	−0.011	0.717
Membership	0.179	0.384	0.251	0.434	0.071	0.000
Ln (rice area)	−0.679	1.138	−0.529	1.611	0.151	0.007

Notes: S.D represents the standard deviation.

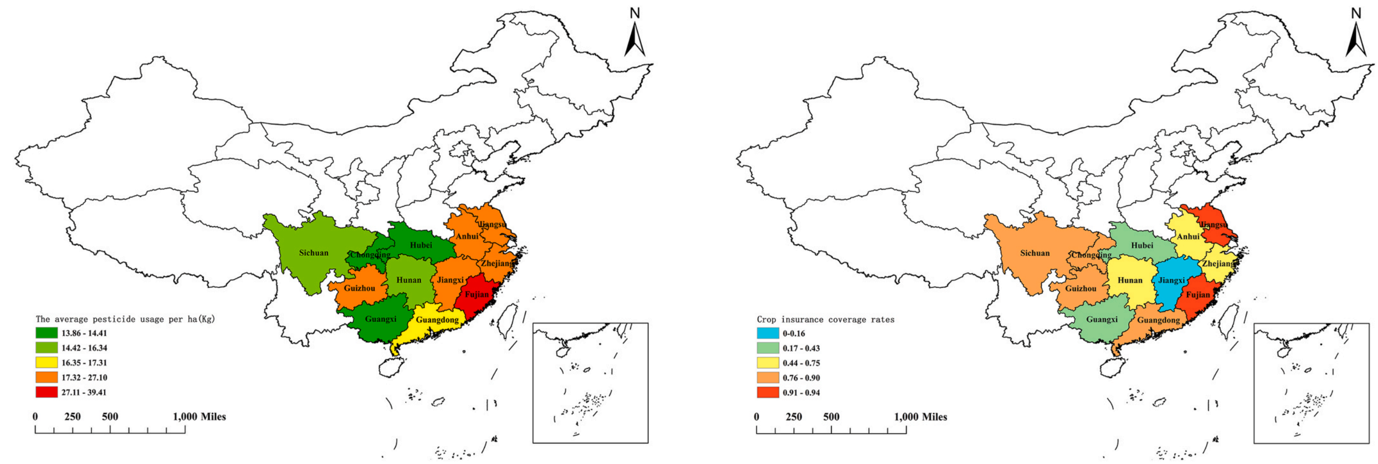

Fig. 3. Comparison among provinces. (a). The average pesticide use per ha; (b). The crop insurance coverage rates.

pesticides, including Sichuan, Chongqing, Hunan, and Guangdong. Nevertheless, it should be further verified by empirical strategies.

4.2. Benchmark analysis

Table 3 presents the results of benchmark regression, including the OLS estimation and the CF approach. Using the OLS estimation, for farmers who have purchased crop insurance, the use of pesticides has been reduced by about 20.4% at a 1% level of significance. In the CF approach, the residual is significant at a 1% level, meaning that crop insurance is endogenous. Therefore, we took the estimates of the CF approach as our preferred benchmark results. We included provincial and time fixed effects to capture any regional and time impacts that may affect crop insurance and pesticide application. The results of the CF approach show that the purchase of crop insurance decreases pesticide use by 33.30%[2] on average. The results are contrary to the study of Chang and Mishra (2012), which obtained the positive effect of agricultural insurance on agrichemical application through a quantile regression. And it is different from the study carried out by Mishra et al. (2005), which concluded that insurance did not significantly change pesticide expenditures by winter wheat farmers. It is worth noting that the above studies are based on the United States scenario, and the indicators used to measure pesticide use are inconsistent with that of this paper. These factors might make a different result (Möhring et al., 2020b). Based on the situation in China, the results of this paper are explicable. The research of Chèze et al. (2020) provides a potential explanation. The risk of large production and profit losses due to pests strongly limits farmers' willingness to reduce their pesticide use. Meanwhile, crop insurance can increase the adoption rate of sustainable agricultural production technologies, thus contributing to the rational use of pesticides by farmers to some extent (Brick and Visser, 2015; Farrin and Miranda, 2015; Carter et al., 2016). In conclusion, crop insurance gives farmers an incentive to reduce pesticide use and adopt some eco-friendly agricultural technologies.

Estimates in Table 3 also show that the age of the household head, household assets per capita, family size, and agricultural laborers within the household have a negative relationship with pesticide use. On the contrary, rice cultivation experience, risk perception, and rice area have significant impacts on pesticide use. These estimates are in line with the literature which found the factors affecting pesticide use (Cai and Han, 2012; Fan et al., 2015; Zhao et al., 2018; Sharafi et al., 2018; Schreinemachers et al., 2020; Guo et al., 2021).

Table 3
The results of benchmark regressions.

Variables	Ln (pesticide use)	
	OLS	CF
Insurance	−0.204***	−0.405***
	(0.040)	(0.070)
Residual		0.166***
		(0.050)
Gender	−0.070	−0.060
	(0.048)	(0.047)
Age	−0.013***	−0.011***
	(0.004)	(0.004)
Schooling	−0.011*	−0.009
	(0.006)	(0.007)
Health	−0.043	−0.033
	(0.042)	(0.043)
Experience	0.007***	0.007***
	(0.002)	(0.002)
Training	−0.046	−0.032
	(0.044)	(0.044)
Risk perception	0.316***	0.314***
	(0.031)	(0.032)
Ln (assets)	−0.137***	−0.128***
	(0.024)	(0.025)
Family size	−0.022**	−0.018*
	(0.010)	(0.010)
Agricultural laborers	−0.110***	−0.113***
	(0.024)	(0.024)
Membership	0.049	0.066
	(0.041)	(0.042)
Ln (rice area)	0.042***	0.043***
	(0.015)	(0.015)
Provincial fixed effect	*yes*	*yes*
Time fixed effect	*yes*	*yes*
Constant	4.952***	4.890***
	(0.380)	(0.378)
Hansen J statistic (P-value)		0.177
Endogeneity test (Chi-sq (1) P-value)		0.000
Cragg-Donald Wald F statistic		717.936***
Observations	3,410	3,410
Adjusted R-squared	0.130	0.133

Notes: ***, **, * denote significance at 1% level, 5% level, and 10% level. Coefficient estimates are shown with robust standard errors in parentheses. In columns CF standard errors are bootstrapped with 1000 replications. OLS, ordinary least squares; CF, control function estimator.

[2] The insurance' regression coefficient of −0.405 by the CF approach in Table 3 is an absolute number because of the logarithmic processing. Technically, the effect of crop insurance on pesticide use should be converted to $e^{-0.405} - 1 = -0.3330$.

4.3. Robustness check

4.3.1. Endogenous treatment-effects estimation

To ensure the robustness of the former estimation, this paper introduced the endogenous treatment-effects estimator to verify the effect of crop insurance on pesticide use. Table 4 reports the results of the treatment-effects estimation, showing that the ATE is consistent with that in the CF approach. More specifically, the ATE is −0.502 after controlling for observable characteristics, suggesting that if farmers purchase crop insurance, the pesticide use could be reduced by 50.2%. It further confirms our finding that the purchase of crop insurance can significantly reduce pesticide use by rice farmers.

4.3.2. Heteroscedasticity-based identification strategy

This paper also employed Lewbel's heteroscedasticity-based identification strategy to estimate the effect of crop insurance on pesticide use. First, to address the endogeneity problems of crop insurance, we took the proportion of crop insurance purchases in the village where the household is located and the distance from the farmer to the village committee as two instrumental variables and estimated the effect by using the standard IV method. In Table 5, results in column (1) show that crop insurance can reduce pesticide use by 52.7% and is significant at a 1% level.

Second, column (2) reports the results of the heteroscedasticity-based identification strategy. We use the subset of control variables to construct internal instrumental variables, and estimate the effect by employing the two-stage least squares (2SLS) regression. The result of the Breusch-Pagan test is significant at a 1% level, implying that the error term of the regression equation of crop insurance to pesticide use is heteroscedastic, which satisfies the condition of the heteroscedasticity-based identification strategy. The F-statistics is 19.94, exceeding the conventional "rule of thumb" with an F-statistics of 10. Thus, the internal instruments are strong enough. Additionally, the p-value of Hansen J statistics is not significant, showing that the internal instruments are valid. Results in column (2) suggest that crop insurance decreases pesticide use by 131.8%.

Third, combining methods from columns (1) and (2), the estimation method of Lewbel + IV in column (3) simultaneously involves internal instrumental variables and external instrumental variables. Similarly, all instrumental variables passed the test of weak instrumental variables, and are valid. The results also show that crop insurance reduces pesticide use. As alluded to above, we are confident that the results in this paper are robust.

Table 4
The results of the treatment-effects estimation.

Variables	ATE	POmean	OME0	OME1
Treated vs Control	−0.502*** (0.092)			
Control		3.118*** (0.083)		
Treated		2.617*** (0.039)		
Gender			−0.025 (0.074)	−0.064 (0.057)
Age			−0.011* (0.006)	−0.014*** (0.005)
Schooling			0.026** (0.011)	−0.025*** (0.007)
Health			−0.015 (0.059)	−0.037 (0.056)
Experience			0.014*** (0.004)	0.005* (0.003)
Training			0.097 (0.067)	−0.186*** (0.057)
Risk perception			0.235*** (0.050)	0.317*** (0.038)
Ln (assets)			−0.062* (0.037)	−0.127*** (0.030)
Family size			−0.014 (0.015)	−0.018 (0.012)
Agricultural laborers			0.007 (0.035)	−0.158*** (0.028)
Membership			0.062 (0.082)	0.073 (0.046)
Ln (rice area)			−0.053 (0.033)	0.053*** (0.016)
Provincial fixed effect			*yes*	*yes*
Time fixed effect			*yes*	*yes*
Constant			3.684*** (0.531)	5.011*** (0.501)
Observations	3,410	3,410	3,410	3,410

Notes: POM represents the potential-outcome means; OME0 represents the untreated potential-outcome equations; OME1 represents the treated potential-outcome equations; ***, **, * denote significance at 1% level, 5% level, and 10% level. Robust standard errors are presented in parentheses.

Table 5
The results of the heteroscedasticity-based identification strategy.

Variables	(1) Standard IV	(2) Lewbel	(3) Lewbel + IV
Insurance	−0.527*** (0.067)	−1.318*** (0.408)	−0.559*** (0.065)
Control variables	*yes*	*yes*	*yes*
Provincial fixed effect	*yes*	*yes*	*yes*
Time fixed effect	*yes*	*yes*	*yes*
Constant	3.046*** (0.050)	3.602*** (0.285)	3.071*** (0.048)
Adjusted R-squared	0.110	0.113	0.116
F statistic	26.53	19.94	27.34
Breusch-Pagan (p-value)	–	0.000	0.000
Hansen J statistic (p-value)	0.177	0.746	0.145
Endogeneity test (p-value)	0.000	0.001	0.000
Cragg-Donald Wald F statistic	>15	>15	>15
Observations	3,410	3,410	3,410

Notes: ***, **, * denote significance at 1% level, 5% level, and 10% level. Robust standard errors are presented in parentheses.

4.4. The analysis of moderating effects

The above results indicate that some control variables are related to the significant differences in farmers' pesticide use. To identify the heterogeneous effect of crop insurance on pesticide use, we introduced some key variables (including rice cultivation training, experience, schooling years, and agricultural laborers) to interact with the independent variable of crop insurance, then processed it by the CF approach. The results are presented in Table 6, showing that training, experience, schooling, and agricultural laborers have moderating effects on the negative correlation between crop insurance and pesticide use. Furthermore, the following figures are described to analyze the moderating effects.

Fig. 4 shows the moderating effect of rice cultivation training. Crop insurance has a greater negative impact on the pesticide use by farmers who participated in rice cultivation training than those who did not. The result is consistent with Timprasert et al. (2014), Khan et al. (2015), Jallow et al. (2017), and Kabir et al. (2020). On the one hand, farmers who received cultivation training can acquire knowledge about the safe and rational application of pesticides (Sharma et al., 2015), and even grasp and apply eco-friendly methods to control pests and diseases, such as Integrated Pest Management (IPM) (Jallow et al., 2017). On the other hand, they are more deeply aware of problems about human health and environmental pollution caused by excessive pesticide use (Hashemi et al., 2012). Therefore, rice cultivation training strengthens the effect of crop insurance in pesticide reduction.

Fig. 5 presents the moderating effect of the rice cultivation experience, showing that the treatment effects grow stronger with the increase in rice cultivation experience. That is, the negative effect of crop insurance on pesticide use is stronger for farmers with more experience in

Table 6
The results of moderating effects.

Variables	Ln (pesticide use)	Ln (pesticide use)	Ln (pesticide use)	Ln (pesticide use)
Insurance	−0.035	−0.070	−0.106	0.001
	(0.112)	(0.130)	(0.135)	(0.129)
Insurance × Training	−0.444***			
	(0.087)			
Insurance × Experience		−0.011***		
		(0.003)		
Insurance × Schooling			−0.040***	
			(0.014)	
Insurance × Agricultural laborers				−0.189***
				(0.045)
Residual	0.144***	0.154***	0.182***	0.150***
	(0.050)	(0.050)	(0.050)	(0.050)
Control variables	*yes*	*yes*	*yes*	*yes*
Provincial fixed effect	*yes*	*yes*	yes	*yes*
Time fixed effect	*yes*	*yes*	*yes*	*yes*
Constant	4.678***	4.699***	4.680***	4.575***
	(0.394)	(0.394)	(0.393)	(0.394)
Observations	3,410	3,410	3,410	3,410
R-squared	0.147	0.142	0.142	0.144

Notes: ***, **, * denote significance at 1% level, 5% level, and 10% level. Robust standard errors are presented in parentheses, standard errors are bootstrapped with 1000 replications.

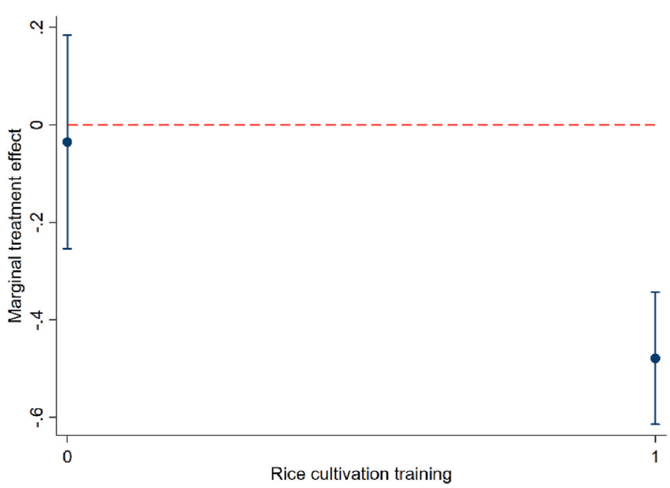

Fig. 4. The moderating effect of rice cultivation training.

rice cultivation. Some studies showed that farmers' cultivation experience is an important factor for the overuse of pesticides (Khan and Damalas, 2015; Bagheri et al., 2019; Huang et al., 2020). On the one hand, farmers' traditional use of pesticides is deeply rooted, and they often judge pesticide use based on subjective experience (Huang et al., 2020). On the other hand, most farmers gain agricultural production experience mainly through their explorations and exchanges with their parents, but their farming methods are not updated on time (Khan and Damalas, 2015). As a result, farmers with richer cultivation experience are more likely to use excessive quantities of pesticides. Due to the existence of the substitute effect, the negative impact of crop insurance on pesticide use by farmers with richer cultivation experience is significant.

Fig. 6 plots the moderating effect of schooling years, meaning that the negative impact of crop insurance on pesticide use is gradually augmented with the increase of the schooling years. There are several

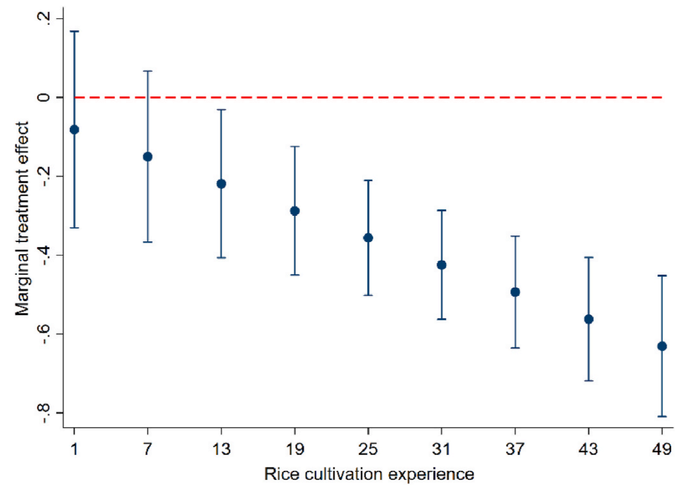

Fig. 5. The moderating effect of rice cultivation experience.

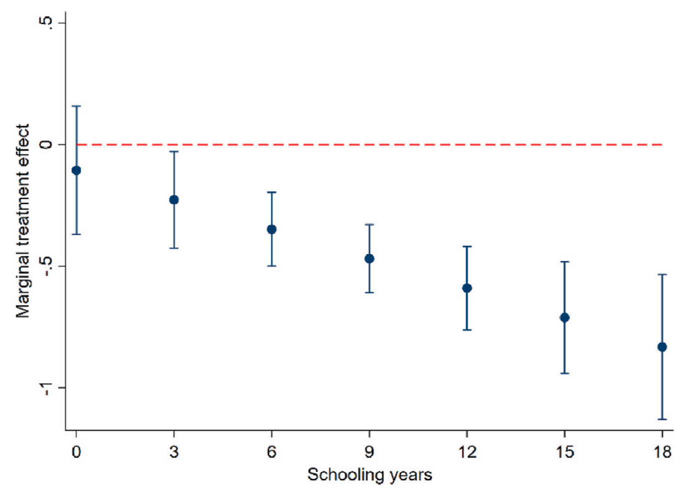

Fig. 6. The moderating effect of schooling years.

possible reasons for this result. First, farmers with a higher level of education can better understand pesticide instructions and master the methods of applying equipment so that they can use pesticides safely and rationally (Sharifzadeh and Abdollahzadeh, 2021). Second, better-educated farmers have better judgment and are less prone to be influenced by the advice of pesticide retailers (Ali et al., 2013; Sharafi et al., 2018). Third, well-educated farmers will be more receptive to the concept of sustainable development and awareness of the negative effects of pesticide overuse on health and the environment (Hashemi et al., 2012; Pan et al., 2021). Therefore, they tend to adopt some clean production practices such as adopting Integrated Pest Management (IPM), organic and green production techniques. (Khan et al., 2015; Jallow et al., 2017).

Fig. 7 demonstrates the moderating effect of agricultural laborers within the household, showing that the more agricultural laborers within the household, the stronger impact of crop insurance on pesticide use is. As factors of agricultural production, there is a certain substitution relationship between pesticides and labor. More agricultural laborers in the household allows farmers to better manage field production, for example, replacing herbicide applications with manual weeding (Lai, 2017). That is, a larger agricultural labor force can meet the demand in labor inputs for sustainable agricultural practices (Teklewold et al., 2013). As a result, agricultural laborers within the household can reinforce the negative relationship between crop insurance and pesticide use.

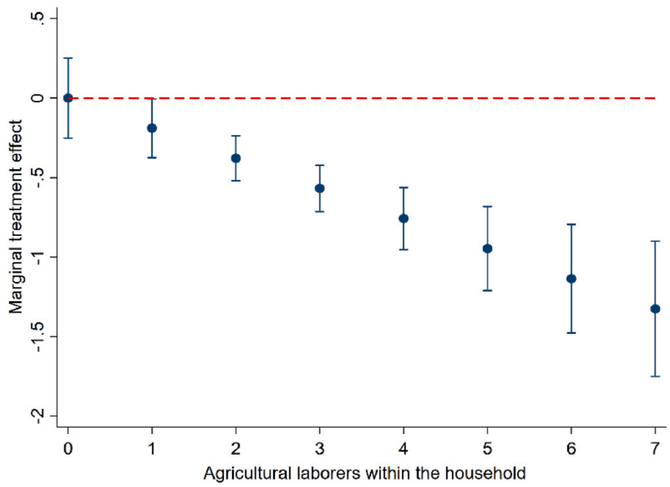

Fig. 7. The moderating effect of agricultural laborers within the household.

4.5. Heterogeneous effects from unobservable characteristics

Due to the unobservable characteristics of individual ability, risk preference, and expectations, farmers respond differently to crop insurance. Inspired by Heckman and Vytlacil (1999), the 99 percentage points of the distribution of unobservable U_D and the corresponding marginal treatment effects (MTEs), and the average treatment effect (ATE) line are portrayed in Fig. 8. The smaller the U_D is, the higher probability that farmers on the margin of crop insurance purchase have. The upward-sloping MTE curve suggests that farmers who are more likely to buy crop insurance apply fewer pesticides, whose MTE is lower than the ATE value of −0.46. Instead, the treatment effect of crop insurance is weaker for farmers with a lower likelihood of purchasing crop insurance. The reason might be that farmers on the margin of crop insurance have unobservable characteristics which impact their decisions, such as risk preference and ability. Farmers who most tend to buy crop insurance is often risk-averse, so they applied more pesticides to avoid risks from pests and diseases. Because the risk of rice production is transferred by crop insurance (Ke et al., 2015; Budhathoki et al., 2019), the treatment effect of crop insurance in pesticide reduction is more significant. Nevertheless, farmers who are less inclined to buy crop insurance may have the ability to apply some agricultural techniques to control crop losses from pests and diseases rather than inputting large pesticides (Rahman et al., 2018; Gao et al., 2019), and therefore the treatment effect of crop insurance is slight. This test proves that the MTE is strongly heterogeneous and suggests that farmers make their selections partially based on unobserved factors.

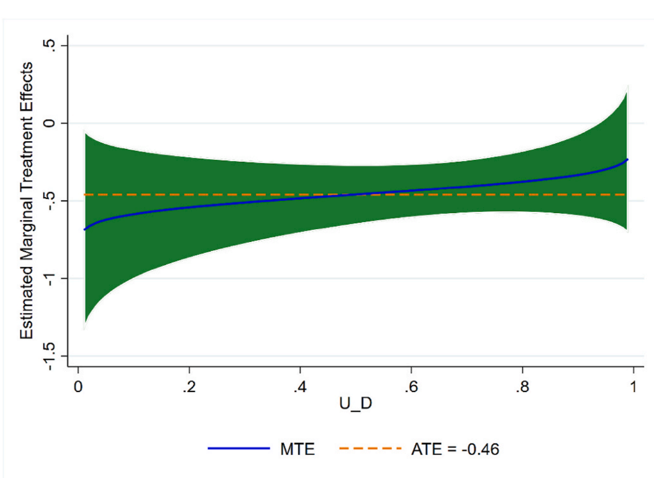

Fig. 8. Estimated MTE of crop insurance on pesticide use.

5. Conclusion and policy implications

The use of pesticides has multiplied the global rice supply, but it also in return impacts our ecological environment and human health. Some effective measures should be taken to limit the overuse of pesticides. Based on the micro-survey data of rice farmers from 12 main rice production provinces in southern China, this paper employs the CF approach to estimate the effect of crop insurance on pesticide use. Empirical results show that crop insurance significantly reduces pesticide use by 33.30%. The negative effect of crop insurance on pesticide use is confirmed by applying the endogenous treatment-effects model and the heteroscedasticity-based identification strategy. Furthermore, the results of moderating effect reveal that rice cultivation training, experience, schooling years, and agricultural laborers within the household can strengthen the negative effect of crop insurance on pesticide use. Finally, we find that the treatment effects for marginal farmers are heterogeneous because the effect of crop insurance on pesticide use is also influenced by unobservable factors such as risk preference and individual ability. For farmers who are most inclined to purchase crop insurance, the MTE is lower than the ATE, meaning that the pesticide reduction effect of crop insurance is the strongest. The contrary is the case for farmers who are most unlikely to purchase crop insurance.

These findings have meaningful implications for mitigating the overuse of pesticides. First, our results indicate that as a formal risk management mechanism, crop insurance can reduce pesticide use significantly. As observed by Jallow et al. (2017), although farmers are aware of the health and environmental risks associated with the overuse of pesticides, they still tend to use more pesticides because they value and worry more about yield losses due to natural disasters. Crop insurance, however, can transfer natural risks and eliminate farmers' concerns. Therefore, government departments should vigorously promote crop insurance and develop targeted insurance plans based on farmers' production needs, thereby mitigating the hazards associated with pesticide overuse.

Second, technical extension departments should provide systematic training to farmers on agricultural production, conveying proper knowledge and use of pesticides, as well as the health and environmental hazards associated with pesticide overuse. More importantly, training courses should teach farmers some production techniques, such as green prevention and control techniques, organic production techniques, and even artificial intelligence-based precision application techniques. Of course, the above measures are taken difficultly without formal basic education, although it will take a long-term effort to improve the education level in rural areas. Compulsory education in rural areas in China has achieved great success in the past three decades, and the education level of the rural population will be significantly increased in the future, which will help farmers understand the knowledge and technology related to agricultural production and operation.

Third, this paper reveals that an increase in agricultural labor in households can reinforce the negative effect of crop insurance on pesticide use. However, developing countries like China have been facing issues of large rural-urban migration in the process of industrialization and urbanization, leading to a decrease in the rate of employment in agriculture (Van den Berg et al., 2007). In fact, one of the main reasons for this phenomenon is the high opportunity cost of agricultural production. Many studies have shown that producing safe and certified agricultural products can increase farmers' earnings and bring considerable health, environmental and social benefits (Pretty and Bharucha, 2015; Rahman et al., 2018; Gao et al., 2019). Hence, the government should encourage agricultural companies and farmers' organizations to participate in food quality and safety certification such as green and organic certification, and lead small-scale farmers to produce high-quality and high-value agricultural products, which in turn could attract more people to engage in sustainable agricultural production.

This study has some limitations. Since continuous tracking surveys are difficult, we could not perfectly address the estimation bias due to omitted variables. In addition, relevant agricultural policies may influence the pesticide reduction effect of crop insurance, so future studies could focus on this aspect. Finally, future studies could also be extended to other countries and regions with different agricultural development patterns to further explore the effects and mechanisms of agricultural insurance in pesticide reduction.

Credit author statement

Houjian Li: Conceptualization, Investigation, Data Collection, Methodology, Software, Reviewing and Editing. **Kaihua Yuan**: Conceptualization, Methodology, Reviewing and Editing, **Andi Cao**: Methodology, Writing- Reviewing and Editing. **Xuemei Zhao**: Writing – original draft, Writing- Reviewing and Editing, **Lili Guo**: Conceptualization, Methodology, Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table I
The variable definitions

Variables	Definitions
Dependent variables	
Pesticide use	The average dosage of pesticides per ha (kilogram).
Ln (pesticide use)	The natural logarithm of the average dosage of pesticides per ha.
Independent variables	
Insurance	1 if the household purchased crop insurance, 0 otherwise.
Instrument variable	
Insurance proportion	The proportion of crop insurance purchases in the village where the household is located (%).
Distance	Distance from the farmer to the village committee (kilometer).
Control variables	
Gender	1 if the household head is male, 0 otherwise.
Age	The age of the household head (years).
Schooling	The number of years of formal education for household head (years).
Health	1 if the health of the household head is bad; 2 if the health of the household head is general; 3 if the health of the household head is good.
Experience	Years of the household's rice cultivation (years).
Training	1 if household head has participated in rice cultivation training, 0 otherwise.
Risk perception	Risk perception level of rice pests and diseases of the household head. 1 if the risk perception level is high, 0 if the risk perception level is low.
Assets	The household assets per capita (yuan).
Ln (Assets)	The natural logarithm of the household assets per capita.
Family size	The total population of family.
Agricultural laborers	The number of agricultural production laborers in the household.
Membership	1 if the household joined a rural cooperative, 0 otherwise.
Rice area	The total area of rice cultivation (ha).
Ln (rice area)	The natural logarithm of the total area of rice cultivation.

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