Effects of Haze Pollution on Pesticide use by Rice Farmers: Fresh Evidence from Rural Area of China

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Effects of haze pollution on pesticide use by rice farmers: Fresh evidence from rural area of China

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Abstract: Recently, serious haze pollution has not only threatened the human health and food security, but also seems to have aggravated the unscientific use of pesticides by rice farmers in rural area of China. Using original data on haze pollution across China, combined with rural household survey data collected from 2014 to 2018, we conducted a detailed empirical study on the effects of haze pollution on pesticide use by rice farmers based on the theory of risk aversion. The empirical results revealed that haze pollution with higher levels of $PM_{2.5}$ positively impacted the use of chemical pesticides in the rice cultivation. More precisely, with 1% increases in $PM_{2.5}$ concentration, the amount of pesticide application per mu increased by 7.9%, and the average pesticide fee per mu increased by 2.3%, respectively. The results were robust to a series of tests that addressed potential endogeneity concerns, including omitted variable bias, measurement error and reverse causality. We then examined the heterogeneous effects of haze pollution increase on the use of chemical pesticides and found that the effects of haze pollution on the use of chemical pesticides to be weaker for rice farmer with more rice-planting experience, those with smaller cultivated area of rice, however, the effects on the amount of chemical pesticide application per mu to be weaker for those with rice insurance, but the effects on the average chemical pesticide fee per mu to be stronger for those with rice insurance. Our findings provide important policy implications for pesticide risk management in rural areas of developing countries.

Keywords: haze pollution; pesticide use; rice production; approximately perfect instrumental variable

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1. Introduction

As a meteorological concern, haze pollution has attracted worldwide attention in recent years. Especially in China, haze pollution has become one of the major atmospheric pollution problems (Li et al. 2016; Ye and Zhou 2015; Zhang et al. 2019), commonly attributed to increased pollutant emissions caused by China's rapid economic development (Cai et al. 2017). The main component of haze is dust particles suspended in the air, and particle size and composition are of central importance in defining the adverse human health effects of particulate matter(Thurston, et al., 1994). The additional atmospheric particle load during the hazy episodes is predominantly due to an increase of the fractions below or equal to 2.5 microns in diameter ($PM_{2.5}$) (Heil and Goldammer, 2001). The chemical composition of fine particles mainly includes organic carbon (OC), element carbon (EC), nitrate (NO_3^-), sulfate (SO_4^{2-}), and ammonium salt (NH_4^+) (Hou et al., 2011; Tan et al., 2009). Air pollution caused by these inhalable particles ($PM_{2.5}$) not only leads to physical health damage but also exerts adverse effects on people's psychology, emotions and behavior (Qiu et al., 2020). Haze pollution generally offsets any increase in subjective well-being brought about by economic growth because it threatens people's physical and mental health (Song et al., 2019). Furthermore, air pollution has negative impacts on food security. It not only affects plant growth and animal health, but also changes the market balance of agricultural inputs and outputs in the food supply chain, thus indirectly affecting food security (Sun et al. 2017). Rice is a major staple food for half of the world's population (Lu and Li 2006; Wing et al. 2018), and it has been a significant icon of Chinese culture for thousands of years(Hung, 2014).The evidences above shows that severe haze not only affects rice safety, it also introduces diseases for human beings through the food chain.

This study aimed to contribute to this growing area of research by exploring the effects of haze

pollution on the use of pesticides by rice farmers. Rice production is a diffuse source of pollutants (Chapagain and Hoekstra, 2011), and cleaner rice production is an important issue in today's society (Kim et al., 2014). Pesticides are used as the primary method of pest control, but they have a negative effect on human health (Pingali, 1994) and adverse consequences for the environment (Gerpacio,1997; Mahdavi et al., 2015). Several previous studies showed that excessive use of pesticides make production riskier (Salazar Espinoza and Rand, 2019). Farmers who frequently spray pesticides are more likely to have headaches, nausea, and skin problems, and long-term exposure to pesticides has a significant invisible impact on farmers' neurological, liver, and kidney systems (Qiao et al., 2012). Therefore, to insure farmers' health and maintain the balance of the environment, great care must be taken in the use of pesticides (Nouri et al., 2000).

In the past, various scholars have conducted extensive research on the harm caused by haze and reached a series of effective conclusions. On the one hand, haze causes farmers to suffer from respiratory diseases (Kurata et al., 2020), and osteoporosis (Qiao et al., 2020), and even increases the human mortality rate (Cheung et al., 2020; Fan et al., 2020; He et al., 2016). On the other hand, haze leads to the deterioration of air quality (Wang et al., 2016), and the increased air pollution may increase the probability of violent crime (Burkhardt et al., 2019; Chen and Li, 2020). In addition to the above hazards, haze has other effects. First, the increased investor attention to haze decreases stock market returns (Zhang and Tao, 2019). Second, residents have a powerful motivation to adopt energy-saving measures under the influence of haze pollution (Zhao et al., 2019). Third, $PM_{2.5}$ reduces the subjective well-being of Chinese residents by affecting their physical health (Shi and Yu, 2020).With an increase of the density of the particles like $PM_{2.5}$, the rates of overweight and obesity significantly increase (Deschenes et al., 2020). Although there have been many studies

concerning haze, few studies have examined the effects of haze on pesticide use by rice farmers. This may cause people to ignore the indirect impact of haze on rice safety and human health from the perspective of pesticide use, posing a great threat to human survival.

To fill this research gap and attract the government's attention to the harm of haze on rice safety, we examined the effects of haze pollution on the pesticide use by rice farmers base on the theory of risk aversion. This study made an important contribution by using prefecture-level city data on haze provided by the Chinese Research Data Services Platform (CNRDS), combined with household-level data on pesticide use collected from a survey of 5,403 rice farmers from 12 provinces of China conducted by the Rural Economics Research Center of the Ministry of Agriculture from 2014 to 2018, to assess the impact of haze on the use of pesticide by rice farmers. We found that high levels of $PM_{2.5}$ faced by rice farmers were positively associated with increased pesticide use. Our baseline results showed that a 10% increase in $PM_{2.5}$ concentration increased the amount of pesticide application per mu by 0.15 percentage points, and the average pesticide fee per mu by 0.02 percentage points. We then conduct additional tests to address the potential endogeneity issue. First, we used a control function approach (CFA) with an instrumental variable the air flow intensity of the prefecture-level city to address potential endogeneity issues, and continued to find that $PM_{2.5}$ concentration increases had a large and statistically significant effect on the use of pesticide by rice farmers. More precisely, a 10% increase in $PM_{2.5}$ concentration increased the amount of pesticide application per mu by 0.79 percentage points, and the average pesticide fee per mu by 0.23 percentage points. Second, we randomly divided the total samples into two equal parts, using the data from one part to estimate the casual impact of haze on the use of pesticide with control function approach, and repeated the above procedures 1000 times. We checked the distribution of the CF

estimator of the $PM_{2.5}$ concentration coefficient and found that the difference between these coefficients was not statistically significant, and the coefficients were clustered around the value of the $PM_{2.5}$ concentration coefficient estimated from the total sample, suggesting that the results were robust in the presence of omitted variables. Third, based on Conley, Hansen, and Rossi's (2012) plausibly exogenous inference and Nevo and Rosen's (2012) imperfect IV inference, we imposed bounds on an endogenous variable of PM2.5 concentration and found that the results were robust. Furthermore, using Lewbel's instrumental variable approaches to control for unobservable characteristics, we found a statistically significant relationship between $PM_{2.5}$ concentration and the use of pesticides by rice farmer.

We then studied the heterogeneous effects across different characteristics of rice farmers and found that the effects of $PM_{2.5}$ concentration increases on the amount of chemical pesticide application per mu were weaker for rice farmers with rice insurance, but the effects on the average chemical pesticide fee per mu were stronger for those with rice insurance. We also found the effects on the usage of chemical pesticides were weaker for farmers with more rice-planting experience farmer, those with smaller scale rice-planting. These conclusions have important implications for the formulation of policy designed to promote pesticide reduction effectively in agricultural production in China.

Our study related to the empirical studies on the determinants of pesticide use. These researchers studied the role of internal factors, such as output and loss expectation(Chèze et al., 2020; Damalas and Koutroubas, 2018; Rosenheim et al., 2020), risk preference(Liu and Huang, 2013; Gong et al., 2016), knowledge and awareness (Fan et al., 2015; Jallow et al., 2017; Schreinemachers et al., 2017; Zhang et al., 2015), farm size(Rahman, 2013; Rahman,2015; Wu et

al., 2018; Qin and LÜ,2020; Zhu and Wang, 2021), and gender and age (Ahmed et al., 2011; Atreya, 2007; Damalas and Hashemi, 2010).They also studied external factors, such as crop insurance(Chakir and Hardelin, 2014;Goodwin et al., 2004; Möhring et al., 2020; Shi et al., 2019) and influences of pesticide retailers(Yang et al., 2014). However, none of these studies analyzed the effect of $PM_{2.5}$ concentrations on the use of pesticide and we aimed to address this deficiency in the existing literature from the perspective of air quality.

The rest of the paper is organized as follows. Section 2 discusses the main action mechanisms of haze affecting pesticide use by rice farmers. Section 3 describes the data and methods of this study. The estimation results and empirical analysis are presented in section 4. Section 5 is the conclusions and Section 6 summarizes the policy implications and limitations.

2. Theoretical analysis

Pesticides play an important role in the agricultural production (Vashishth et al., 2017). The rationale for their use is that they reduce the yield and quality losses caused by pest infestations and bring benefits to farmers ((Chèze et al., 2020; Damalas and Koutroubas, 2018 ; Kishor et al., 2011). Though, the powerful chemicals used to kill pests have raised concerns that they are agents of environmental pollution and human disease (Sharp,1986); for example, food safety encompasses many kinds of potential hazards in food, one of which is pesticide residue(Ralston et al. 1994). Rice is one of the most important food crops for the people of China (Fan et al., 2001; Yangjie et al., 2017), and pesticides are widely used in rice production (Konstantinou et al., 2006; Li et al., 2018). In developing countries, most smallholder farmers have limited knowledge of the proper handling of pesticides, and uncontrolled use of pesticides can cause serious harm to the environment and human health (Calliera et al., 2013; Ibitayo, 2006; Maumbe and Swinton, 2003; Miller, 2004; Verger

143 and Boobis, 2013); therefore, farmers, policy-makers, and other stakeholders seek tools to
144 quantitatively assess pesticide risks and mitigate pesticide impacts on ecosystem and human health
145 (Zhan and Zhang, 2012).

146 Haze has a significant adverse effect on human health (Navrud, 2001; Odihi, 2008), especially
147 for Chinese residents (Yuan et al., 2018). It not only causes respiratory diseases, but also poses a
148 great threat to agricultural production. The air quality on hazy days is substantially worse than that
149 on normal days (Gao et al., 2015), and the atmosphere plays a key role in plant disease resistance.
150 Field observations in air-polluted areas have shown changes in the number of pests and pathogens
151 (Bell et al. 1993). Insect pests inflict damage to humans, farm animals, and crop yields, and plant
152 pests are considered to destroy one-fifth of the world's total crop yields annually (Kumar et al. 2013).
153 And as we all know, pesticides have been used for many years to treat pests in agricultural fields
154 (Vallamsundar et al. 2016). We could thus infer that, when increased haze leads to frequent
155 outbreaks of disease and insect pests, rice farmers would be encouraged to use more pesticides to
156 eliminate them.

157 To reduce the risks associated with pesticides application in agriculture, resulting in more
158 sustainable agricultural systems, some measures are called for to prevent the spread of the disease
159 (Böcke and Finger 2016). Farmers increasingly use green prevention and control technology for
160 tobacco (Dong et al. 2015) and rice (Dan et al. 2012) cultivation to dispose of pests and diseases.
161 However, haze weakens the effectiveness of most green prevention and control technologies, forcing
162 rice farmers to turn to pesticides. In addition to health problems, high aerosol loads can impact
163 visibility and thus reduce photolysis rates over cities, leading to potential implications for
164 photochemistry (Hollaway et al. 2019; Wang and Wang 2014). This is a serious problem in the

elimination of pests. Pests such as moths fear the light and are inactive in daytime (Burges and Jarrett, 1976). When continuous heavy haze pollution causes insufficient sunshine, it is easy for various diseases and insect pests to proliferate. Farmers then have to increase the use of pesticides to control pests. Further analysis suggested that an increasing intensity of haze in the air makes people choose to stay at home (Yi et al. 2020; Agarwal et al. 2020), thus limiting outdoor work for rice farmers. Under these circumstances, rice farmers are forced to use pesticides as an alternative to outdoor labor; for example, using herbicides instead of artificial weeding.

In summary, haze is a serious problem for rice farmers, posing a huge threat to the environment and human health, forcing rice farmers to use more pesticides to kill pests and remove weeds.

3. Data Collection and Variable Measurement

We combined three different datasets in our analysis. First, we use the survey data from 5,403 samples collected from Chinese rice-producing areas across 70 counties, 30 cities, and 12 provinces during the period of 2014-2018 (see Fig.1). A farm household survey is conducted annually by Rural Economic Research Center of Agriculture Ministry from November to December, and around 20-25 rice farmers are randomly selected from each village on an annual basis. This dataset contained rich information relating to characteristic of rice farmers and households, rice production and technology, the inputs and outputs of rice cultivation, and the management and operation of rice cultivation.

Our second dataset consisted of annual concentrations(micrograms per cubic meter) of ground-level fine particulate matter($PM_{2.5}$) in China at a city level during the period of 2014-2018, which was provided by Chinese Research Data Services Platform. This dataset combined aerosol optical depth

retrievals from multiple satellite instruments. The GEOS-Chem chemical transport model is used to relate this total column measure of aerosol depth to near-surface $PM_{2.5}$ concentrations. Geographically Weighted Regression (GWR) was used with global ground-based measurements to predict and adjust for the residual $PM_{2.5}$ bias per grid cell in the initial satellite-derived values. Our third dataset included information on air flow coefficient at the prefecture-level, which is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF).

Finally, we merged the resulting rice-farmer household dataset with the prefecture-level $PM_{2.5}$ concentration and air flow intensity data using information on the location of rice-farmer household. Our cleaned dataset from 2014 to 2018 includes 5403 household-year observations from 30 cities.

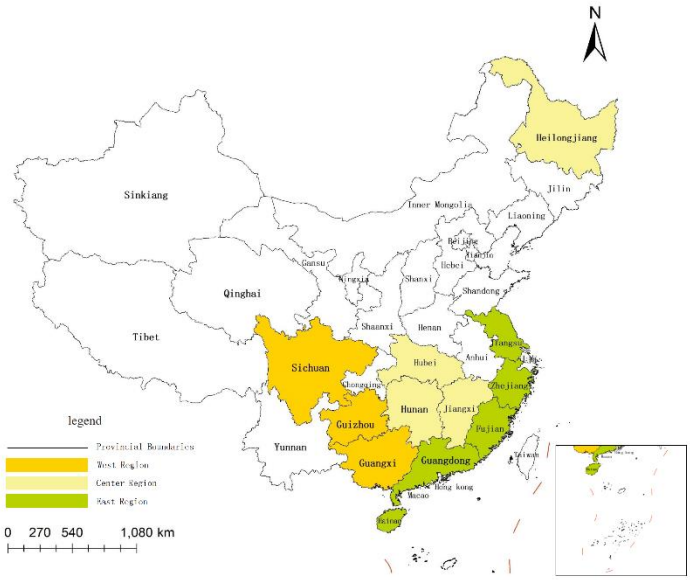

Fig.1 The distribution of selected rice production areas in China

4. Methodology

4.1. Empirical strategy

To obtain the main empirical results, we employed the following economic model to estimate the impact of haze on pesticide use by rice farmers.

$$Y_i = \alpha + \beta \cdot PM_{2.5} + \gamma X_i + \varepsilon_i \quad (1)$$

where i represents the different rice farmers interviewed and Y denotes pesticides used by rice farmers. Because smallholders are the main group of rice farmers in China (Scott et al., 2013), we were concerned that they might lack awareness of the dangers of pesticides and fail to monitor the amount of pesticides they had used. This study therefore chose the average pesticide application amount per mu and the average actual pesticide fee per mu to measure the use of pesticides by rice farmers. $PM_{2.5}$ is the haze concentration in the prefecture-level city where rice farmers live and grow rice crops. X_i is a vector of control variables, and ε_i is the random error term.

In this study, we applied the ordinary least squares(OLS) method to estimate the value of coefficient β, because β represents the effects of haze on pesticide use by rice farmers. However, the omission of some relevant explanatory variables, reverse causality and measurement errors may lead to endogeneity between $PM_{2.5}$ and the random error term ε, making the estimate of coefficient β biased. In this study we further employed the CF approach with an instrumental variable to obtain more accurate estimation results and also perform a series of checks to test the robustness of our results.

4.2 Control Function (CF) Approach

The CF approach is an econometric method of correcting for biases due to selection and/or endogeneity (Amil et al. 2010;Heckman et al. 1985; Johnsson and Moon 2019). The instrumental

variable (IV) and two-stage least squares (2SLS) method are usually used to obtain a more accurate coefficient when the CF approach is selected to deal with the problem of endogeneity (Kim and Kim, 2011; Rummery et al., 1999; Sokbae and Lee 2007). The instrumental variable for this study is the air flow intensity in the prefecture-level city, abbreviated as "amass". The detailed process of CF approach is as follows.

In the first stage, a regression of haze concentration in the region on the instrumental variable was conducted to obtain the residual of the simplified equation:

$$PM_{2.5} = \delta_0 + \delta_1 \cdot \text{amass} + \lambda X_i + \eta_i \tag{2}$$

where amass is the instrumental variable, and the meaning of $PM_{2.5}$ and X_i is the same as for Equation (1).

In the second stage, the residual term in the simplified equation was used as an additional explanatory variable to estimate the main equation—Equation (1):

$$Y_i = \theta_0 + \theta_1 \cdot PM_{2.5} + \theta_3 \hat{v} + \theta_4 X_i + \mu_i \tag{3}$$

where $\hat{v}$ is the residual term from Equation (2), and other symbols have the same meaning as in Equation(1).

If the coefficient θ_3 of residual term $\hat{v}$ in Equation (3) was significant, $PM_{2.5}$ was endogenous. In that case, the residual term $\hat{v}$ would be included in Equation (1) to correct the endogeneity bias of coefficient β in Equation (1). By contrast, an insignificant coefficient θ_3 of residual term $\hat{v}$ meant that $PM_{2.5}$ was exogenous, in which case, the residual term $\hat{v}$ would be excluded from Equation (3) to make a more effective and unbiased estimate (Ogutu and Qaim 2019).

4.3. Imperfect instrument variable

The CF approach combined with the instrumental variable (IV) to estimate the parameters helped to simplify the calculation (Murtazashvili and Wooldridge, 2016). In other words, the CF

approach to handling endogeneity is inherently an instrumental variables method. Constructing a valid CF relies on the availability of one or more instrumental variables (Wooldridge, 2015). In this study, when the instrumental variable is taken into account in the original the OLS model, Equation (1) can be written as follows:

$$Y_i = \alpha + \beta \cdot PM_{2.5} + \omega Z_i + \gamma X_i + \varepsilon_i \tag{4}$$

$$PM_{2.5} = \pi Z_i + V_i \tag{5}$$

A qualified instrumental variable should satisfy two properties. One is validity, also known as exclusion restriction, which means that instrumental variables can only indirectly affect dependent variables by affecting endogenous variables ($Cov(Z_i, \varepsilon_i)=0$). The other is strong instrumentality, which means that the correlation should be strong between instrumental variables and endogenous variables, or is otherwise called a weak instrumental variable. In reality, however, validity assumptions are inherently untestable and inferential. One way to loosen the IV assumptions is to remove the assumption that ω is precisely equal to 0 (Damian Clarke, 2018). The IV estimator remains valuable as long as it is plausibly exogenous(i.e. $\omega \approx 0$). In other words, the constraints of this approach on the instrumental variables still exist, but the instrumental variables go from perfectly exogenous to plausibly exogenous.

Two methods were proposed by Conley, Hansen, and Rossi (2012) to loosen IV assumptions: the union of confidence interval (UCI) method and the local to zero (LTZ) method. In terms of concrete operations, the UCI method moves the instrumental variable term in Equation(4) to the left side of the equation to construct a new equation form. It then requires users to specify the maximum and minimum values that ω can take. These values can be symmetric or asymmetric around 0. The specific equation is as follows:

$$(Y_i - \omega_0 Z_i - \alpha - \gamma X_i) = \beta \cdot PM_{2.5} + \varepsilon_i \tag{6}$$

$$\omega_0 \in [\omega_{min}, \omega_{max}] \tag{7}$$

Since the values of other variables are known, at a given confidence level, each value of ω we obtained corresponded to an interval estimator of β. This method was simple, but the β interval contained all possible values, making it difficult to obtain valid information. More importantly, we believed that the value of ω is close to zero and the possibility of other values decreased with their distance from zero. We preferred to place more weight on the values of ω close to zero and less weight on the values of ω distant from zero. Conley, Hansen, and Rossi (2012) imposed a distribution on ω to narrow the estimated interval of β by assigning different possibilities of ω at different values, making β conform to the following distribution:

$$\hat{\beta} \sim N(\beta, V_{2SLS}) + A\omega \tag{8}$$

Here $N(\beta, V_{2SLS})$ is the asymptotic distribution of the 2SLS estimator, where $A = \left\{PM_{2.5}{}' \cdot PM_{2.5}\left(Z' Z\right)^{-1} Z' \cdot PM_{2.5}\right\}^{-1} (PM_{2.5}{}' \cdot Z)$ and ω is assumed to follow some arbitrary distribution (F). The later Aω controls the influence of the deviation of W from 0 on the estimation, and this method is called the LTZ method.

In this study, the UCI and LTZ methods were used to test the robustness of our results and obtain more stable and reliable estimations.

4.4 Heteroscedasticity-based identification strategy

Although the CF approach can effectively solve the endogeneity problem of explanatory variables, it is difficult to find perfect instrumental variables. Lewbel (2012) proposed a heteroscedasticity-based identification strategy to solve the endogeneity problem. It only needs to satisfy the condition that the error term is heteroscedasticity and does not even require an instrumental variable. In this study, we applied this method to perform robustness tests to further

prove the robustness of our results.

The details of the method were also simple, involving only two steps. In the first step, H was a vector of internal instrumental variables according to Lewbel (2012), where $\mathrm{H}_i \in \mathrm{X}_i$ or $\mathrm{H}_i = \mathrm{X}_i$. In our case, we select four exogenous variables for H_i, that is gender, age, rice-planting experience, and household size. We then conducted a regression of the exogenous variables H_i on the endogenous variable $PM_{2.5}$:

$$PM_{2.5} = \varphi_0 + \varphi_1 \mathrm{H}_i + \tau_i \tag{9}$$

After the regression, we obtained the residual term $\hat{u}$, and the formula $(\mathrm{H}_i - \overline{\mathrm{H}}_i)\hat{u}$ was constructed as the instrumental variable in the second-stage equation, where $\overline{\mathrm{H}}_i$ was the mean of the vector of exogenous variables. In particular, Lewbel's approach requires that the residual $\hat{u}$ from the first-stage equation must be heteroscedasticity. In the second step, the instrumental variable $(\mathrm{H}_i - \overline{\mathrm{H}}_i)\hat{u}$ was used to estimate the effects of haze on pesticide use by rice farmers:

$$\mathrm{Y}_i = \sigma_0 + \sigma_1 \cdot PM_{2.5} + \sigma_3(\mathrm{H}_i - \overline{\mathrm{H}}_i)\hat{u} + \sigma_4 \mathrm{X}_i + \vartheta_i \tag{10}$$

If the coefficient σ_3 was statistically significant in the Equation (10), then the term of instrumental variable needs to be retained to correct the endogeneity. If the coefficient σ_3 was not significant, then the explanatory variable $PM_{2.5}$ was exogenous and the term for the instrumental variable needs to be removed. Furthermore, the coefficient σ_1 should be focused. If the coefficient σ_1 was almost the same as the estimated result of the CF approach, this indicated that the estimated result of the CF approach was robust.

5. Results and Discussion

5.1 Descriptive statistical analysis

Table 1 describes the characteristics of individuals and households, the details of rice

production and management, and the air quality conditions. First, most of the rice farmers interviewed were male, with an average age of 51 years, and 46.7% of them had junior high school diplomas. Their average per capita household income was 21,093 RMB yuan in the previous year and well above China's annual poverty line of less than 10,000 RMB Yuan, showing that their living conditions were relatively good. Second, the average pesticide application amount per mu was 1.360 kg, and the average actual pesticide fee per mu was 58.1 RMB yuan. The rice farmers interviewed had rich experience in rice planting (average rice planting years was 25.74)，and 81.4% of them had attended training in rice farming techniques. According to the survey results, 87.9% of rice farmers liked to cultivate rice crop, and 70.2% of them had purchased rice insurance, indicating that they were risk averse in cultivating rice crops. However, only 20.1% of rice farmers had joined farmers' cooperatives. Also, the mean of $PM_{2.5}$ was 33.49: lower than 50, indicating that overall air quality was excellent.

Table 1. Summary statistics of dependent and independent variables level values

Definition	Variable	N	Min	Max	Mean	Std. Dev.	Data Sources
Dependent variables							
Average pesticide application amount per mu (kg)	*Pesticide*	4,908	0	94.20	1.360	2.416	*CNRDS*
Average actual pesticide fee per mu (Yuan)	*Pesticide fee*	4,908	0	7.317	0.581	0.414	*CNRDS*
Independent variables							
Haze concentration in the region (mg/m^3)	$PM_{2.5}$	4,908	12.44	69.86	33.49	12.58	*RERC*
Gender(male=1)	*Gender*	4,908	0	1	0.911	0.285	*RERC*
Age (years)	*Age*	4,908	18	65	51.05	8.061	*RERC*
Illiterate (yes=1)	*Edu1*	4,908	0	1	0.0269	0.162	*RERC*
Primary school (yes=1)	*Edu2*	4,908	0	1	0.271	0.445	*RERC*
Junior high school(yes=1)	*Edu3*	4,908	0	1	0.467	0.499	*RERC*
High school degree or equivalent or above(yes=1)	*Edu4*	4,908	0	1	0.235	0.424	*RERC*
Healthy or not(yes=1)	*Health*	4,908	0	1	0.983	0.128	*RERC*
Rice-planting experience (years)	*Experience*	4,908	6	48	25.74	10.86	*RERC*
Accepting Rice cultivation training last year(yes=1)	*Training*	4,908	0	1	0.814	0.389	*RERC*
Having a liking for rice cultivation(yes=1)	*Preference*	4,908	0	1	0.879	0.326	*RERC*

Purchasing crop insurance (yes=1)	*Insurance*	4,908	0	1	0.702	0.457	*RERC*
Per capita household income last year (Yuan)	*Pincome*	4,908	285.7	600000	21093	33285	*RERC*
Renting the crop land(yes=1)	*Rentin*	4,908	0	1	0.315	0.465	*RERC*
Family size (person)	*Hhsize*	4,908	1	15	4.491	1.597	*RERC*
Number of rice farmers in family(person)	*Rlabour*	4,908	0	7	2.064	0.794	*RERC*
farmland size of rice(mu)	*Tarea*	4,908	0.200	3300	49.61	148.1	*RERC*
Participating in rice planting cooperatives(yes=1)	*Membership*	4,908	0	1	0.201	0.401	*RERC*
Implementation of village agricultural technician system(yes=1)	*Vtechnician*	4,908	0	1	0.738	0.440	*RERC*
Topography of the region (km)	*Topography*	4,908	0.00300	2.066	0.654	0.571	*RERC*
Air circulation intensity	*Amass*	4,908	833.9	5022	1954	957.0	*ECMWF*

Notes: *CNRDS* is the short for Chinese Research Data Services Platform, *RERC* for the Rural Economic Research Center of the Ministry of Agriculture and *ERA-Interim* for The European Centre for Medium-Range Weather Forecasts

Haze varies greatly across regions of China; for example, the North China plain is more seriously affected than other regions (Che et al., 2014). We therefore divided China into three parts- the Eastern Region, the Central Region and the Western Region, to further investigate the heterogeneous effect of haze on the use of pesticides by rice farmers. Table 2 reports the descriptive statistics obtained by region. The results showed that the average pesticide application amount per mu was highest in the Eastern Region, followed by the Central Region, and lowest in the Western Region (see Fig.2). This phenomenon coincided with the severity of haze pollution in different regions of China. In other words, the haze pollution was the most serious in the Eastern Region of China (Li et al., 2013; Ke et al., 2018), and the pesticide application amount per mu was also the greatest. Preliminary observations showed that haze conditions and the use of pesticides by rice farmers were positively correlated. Also, the average actual pesticides fee per mu in the three regions was almost the same (see Fig. 3). The reason for this may be that the Eastern Region has a relatively developed economy, more mature production technology, and lower production cost. As a result, the cost of pesticides in the Eastern Region is like that in other regions, although the amount of pesticides used is relatively high.

Table 2

Average pesticide application amount per mu (Pesticide) and average actual pesticide fee per mu (Pesticide fee) in each area

Variable	Area	Obs.	Min	Max	Mean	Std. Dev.
Pesticide dosage	Eastern	2284	0	25.12	1.57	2.10
	Central	1470	0	94.20	1.28	3.05
	Western	1154	0	56.00	1.05	2.01
Pesticide fee	Eastern	2284	0	3.83	0.59	0.42
	Central	1470	0	7.32	0.58	0.44

Western	1154	0	3.65	0.58	0.35

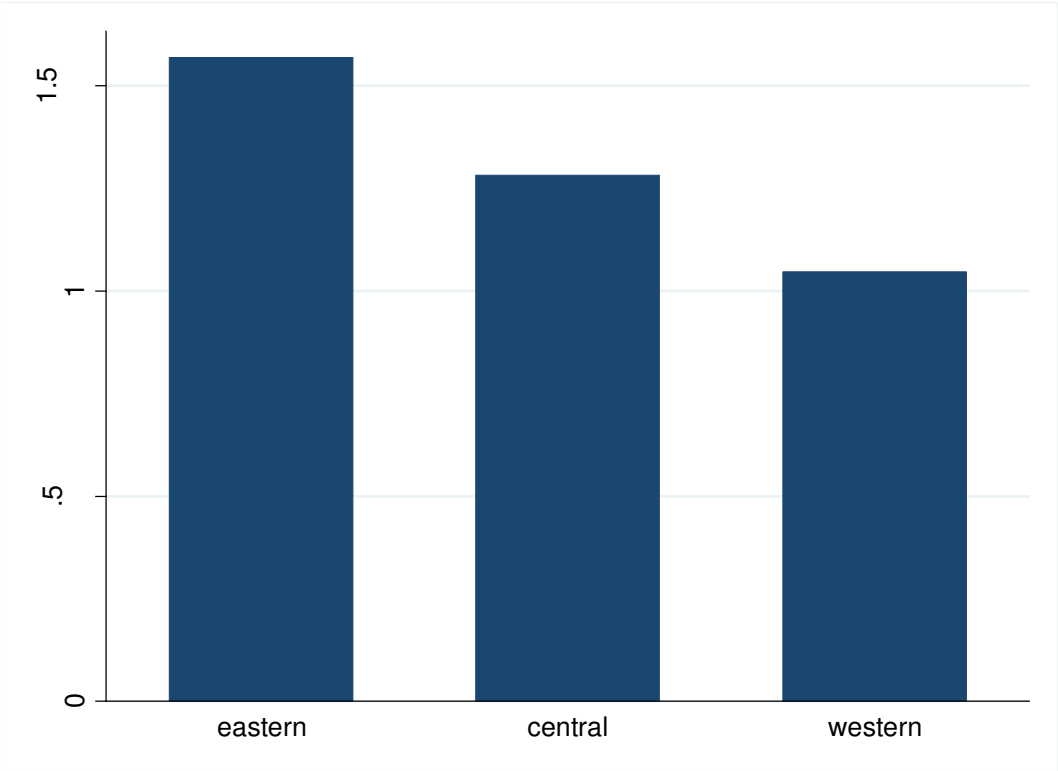

Fig.2 The mean of pesticide dosage per mu in three regions

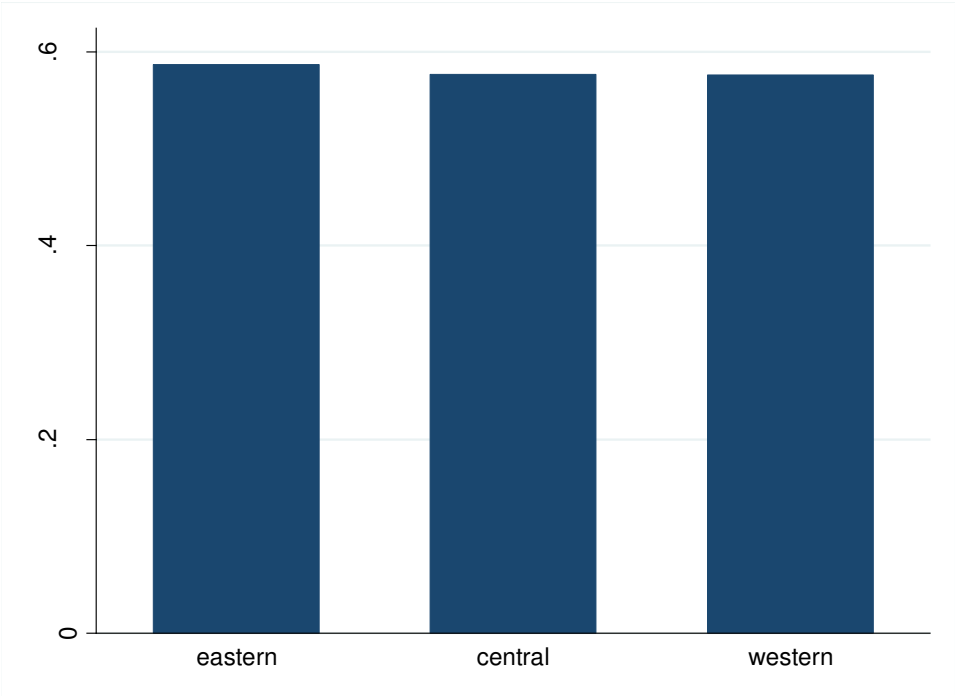

Fig.3 The mean of pesticide fee per mu in three regions

In addition to regional differences in pesticide use and fees, pesticides used by rice farmers in different years were also important. Because air quality is time-variant, by observing changes in pesticide use in different years, we could identify a correlation between haze and the pesticide use by rice farmers across time. Table 3 presents the use of pesticides by rice farmers during 2014-2018. It can be seen that the mean of pesticide application amount per mu was highest in 2017 at 1.47 kg per mu and lowest in 2015 at 1.22 kg per mu(see Fig. 4). The average actual pesticide fee per mu was highest in 2018 at 64 RMB yuan per mu and lowest in 2016 at 53 Yuan per mu (see Fig. 5).

Table 3

Average pesticide application amount per mu (Pesticide) and average actual pesticide fee per mu (Pesticide fee) from 2014 to 2018

Variable	Year	Obs	Min	Max	Mean	Std.Dev.
Pesticide	2014	954	0	94.20	1.46	3.90
	2015	901	0	25.12	1.22	1.89
	2016	1190	0.13	23.63	1.29	1.66
	2017	933	0	49.00	1.47	2.25
	2018	930	0	30.00	1.38	1.77
Pesticide fee	2014	954	0	7.32	0.57	0.47
	2015	901	0	3.83	0.60	0.38
	2016	1190	0.01	3.76	0.53	0.37
	2017	933	0	3.24	0.58	0.42
	2018	930	0	3.65	0.64	0.42

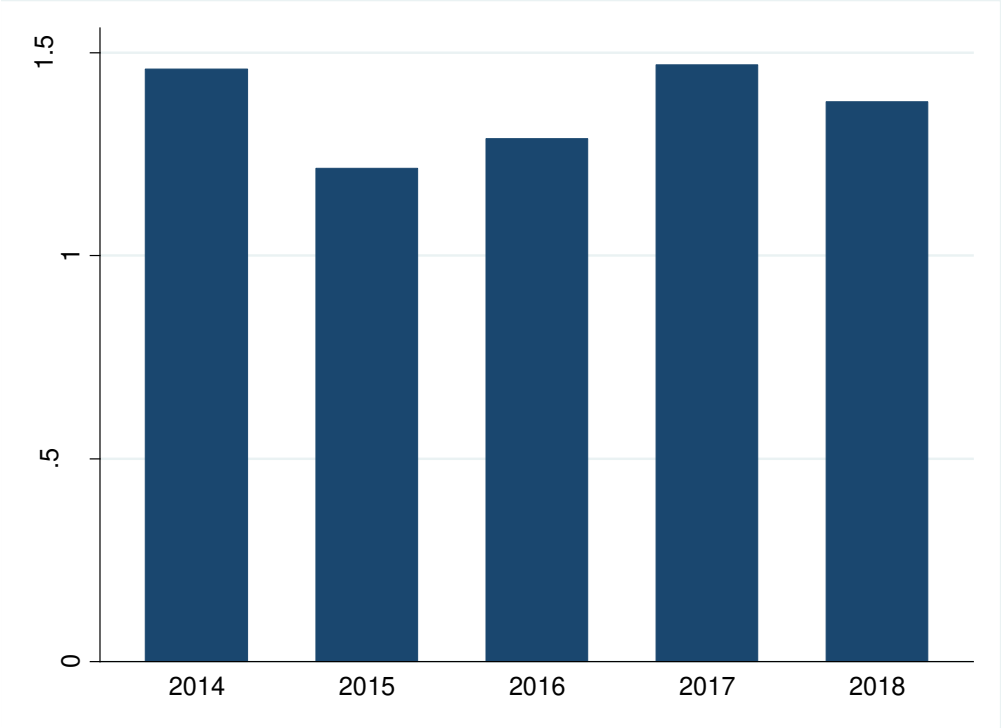

Fig.4 The mean of pesticide dosage per mu during 2014-2018

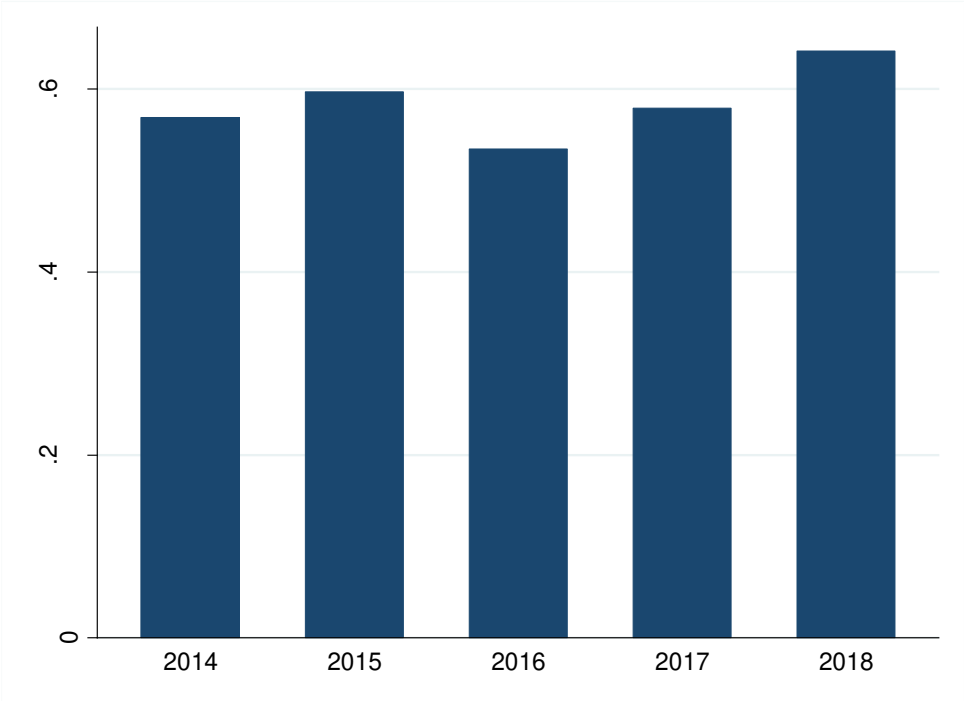

Fig.5 The mean of pesticide fee per mu during 2014-2018

5.2 Benchmark regression analysis

Table 4 reports the results for the effects of haze on pesticide application and pesticide fees, with columns (1) and (3) showing the OLS estimates, and columns (2) and (4) showing the CF estimates. First, we paid special attention to the CF estimates in columns (2) and (4). The estimated coefficients of residuals from the first stage in the fourth row from the bottom of the two columns were both significant at the 1% level, indicating that the explanatory variable $PM_{2.5}$ was endogenous. We retained the residual term in the original equation to correct the endogeneity problem and make the β value in Equation (1) more accurate. In view of this, we mainly analyzed the estimated results using CF approach.

The estimated coefficients for $PM_{2.5}$ in column (2) and (4) were both significantly positive at the 1% level, indicating that the increase in haze pollution was positively correlated with pesticide application and pesticide fee for rice farmers. Specifically, the mass concentration of $PM_{2.5}$ increased by 1 percentage point, the average pesticide application amount per mu would increase by 7.9 percentage points, and the average actual pesticide fee per mu increased by 2.3 percentage points. The underlying mechanisms of haze pollution driving changes in pesticide use might be explained as follows: First, haze pollution can result in a variety of changes in natural conditions such as temperature, light, and humidity (Yang, 2001), having a significant impact on agricultural systems (Zhou & Chen, 2018). Research has suggested that high temperatures may reduce the activity of pesticides and speed up the metabolism of pesticides (Roos & Hopkins, 2011). Humidity can also affect the persistence and efficacy of pesticides (Jonhnsonbc & Youngbg, 2002). Hence, haze pollution can create more survivable conditions for pests and force farmers to use more pesticides. Second, haze pollution increases the health risks of being outdoors (Deschenes et al., 2020) and

weakens the willingness of rice farmers to work outdoors, which pushes the farmers to use more pesticides instead of carrying out outdoor work. Third, farmers are increasingly using green prevention and control technology for tobacco and rice(Dan et al. 2012) cultivation to dispose of pests and diseases, but haze pollution weakens its effectiveness, thus obliging rice farmers to using increasing amounts of pesticides.

From Table 4, we drew the conclusion that age, rice technology training, rice production preferences, the purchasing of rice insurance, and per capita household income were significantly negative at the 1% level, indicating that they had a significant negative effects on pesticide application and pesticide fees. However, family size, rice planting scale and the topography of the region were all significantly positive at the 1% level, indicating that they had significant positive effects on pesticide application and pesticide fees. These conclusions were consistent with other research and may be attributable to older farmers with more experience of pest control for rice production taking better care of their health (Jallow et al., 2017; Wang et al., 2018), meaning that they would be more likely to engage in organic farming than use pesticides. It was obvious that rice farmers who received training (Christos and Spyridon, 2017; Li et al., 2017; Zhou et al., 2020), liked to grow rice crops (Bakker et al., 2020), had agricultural insurance (Yang et al., 2019) and enjoyed a high per capita income (Jin et al., 2017), preferred to reduce the use of pesticides to improve rice production and protect the human health, which was consistent with the previous research (Qin et al., 2020; Möhring et al., 2020; Schreinemachers et al., 2016). Meanwhile, research showed that a large family size usually means greater livelihood pressure, encouraging increased pesticide use to avoid loss. In general, farmers with larger planting areas tended to avoid risks (Feola and Claudia, 2010; Qin et al., 2020) and rely on a stable planting income, making it easy for them to overuse

pesticides (Liu et al., 2018; Migheli, 2017; Qin et al., 2020; Zhao et al., 2018). Another reason for increased pesticide use being influenced by the topography (Hou et al., 2020) is the effect of inconvenient transportation and frequent natural disasters, motivating rice farmers to endeavor to increase marginal rice productivity by increasing pesticide use.

Table 4

The effects of haze on pesticide application and pesticide fee

Variable	Pesticide		Pesticide fee	
	(1)	(2)	(3)	(4)
	OLS	CF	OLS	CF
$PM_{2.5}$	0.015***	0.079***	0.002***	0.023***
	(0.004)	(0.015)	(0.001)	(0.002)
Gender	0.033	-0.038	0.060***	0.036**
	(0.088)	(0.089)	(0.018)	(0.018)
Age	-0.012**	-0.017***	-0.001	-0.003***
	(0.005)	(0.005)	(0.001)	(0.001)
Edu2	-0.465	-0.595	0.027	-0.016
	(0.421)	(0.405)	(0.061)	(0.062)
Edu3	-0.596	-0.683*	-0.007	-0.036
	(0.430)	(0.414)	(0.061)	(0.061)
Edu4	-0.686	-0.691*	-0.012	-0.014
	(0.426)	(0.414)	(0.061)	(0.061)
Health	0.108	-0.053	-0.079	-0.132
	(0.147)	(0.148)	(0.090)	(0.088)
Experience	0.009**	0.009*	0.000	-0.000
	(0.005)	(0.005)	(0.001)	(0.001)
Training	-0.187**	-0.338***	-0.098***	-0.147***
	(0.088)	(0.087)	(0.018)	(0.020)
Preference	-0.445***	-0.673***	-0.047***	-0.122***
	(0.129)	(0.121)	(0.020)	(0.021)
Insurance	-0.197**	-0.376***	-0.045***	-0.104***
	(0.090)	(0.110)	(0.015)	(0.017)
Pincome	-0.094**	-0.287***	0.028***	-0.036***
	(0.041)	(0.055)	(0.008)	(0.010)
Rentin	0.129	0.104	0.057***	0.049***
	(0.115)	(0.113)	(0.015)	(0.015)
Hhsize	0.046**	0.059***	0.011**	0.015***
	(0.020)	(0.021)	(0.004)	(0.004)
Rlabour	-0.067*	-0.055	-0.040***	-0.036***
	(0.037)	(0.035)	(0.008)	(0.008)

Lnarea	0.026	0.126***	0.014**	0.047***
	(0.038)	(0.047)	(0.060)	(0.007)
Membership	0.245***	0.166***	0.043**	0.017
	(0.075)	(0.080)	(0.016)	(0.015)
Vtechinician	-0.034	-0.114	-0.006	-0.033**
	(0.105)	(0.112)	(0.014)	(0.014)
Topography	0.486***	1.314***	-0.008	0.265***
	(0.102)	(0.229)	(0.015)	(0.030)
Regional fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Residual		-0.069***		-0.023***
		(0.015)		(0.002)
Constant	3.175***	3.501***	0.440***	0.548***
	(0.708)	(0.675)	(0.166)	(0.162)
Observations	4908	4908	4908	4908
R-squared	0.027	0.032	0.048	0.067

Notes: Robust standard errors are in the parentheses, and the standard error of CF approach is obtained through repeated sampling of bootstrap for 1,000 times.

*Significant at 10% level, **Significant at 5% level, *** Significant at 1% level.

5.3. Heterogenous effect analysis

To study the heterogeneous effects of haze on the average pesticide application amount per mu and average pesticide fee per mu of rice farmers, this study selected the purchasing of rice insurance, rice planting experience, and the logarithm of rice planting scale to form three interaction terms with haze concentration ($PM_{2.5}$), respectively, and the CF approach was then used for regression analysis. Table 5 shows the CF regression results after adding the interaction terms, with columns (1), (2), and (3) representing the effects of the three interaction terms of $PM_{2.5}$ and rice insurance, rice-planting experience, and the logarithm of planting scale on pesticide application amounts, respectively, while columns (3), (4), and (5) represent their effects on pesticide fees.

First, the estimated coefficients for the interaction term of $PM_{2.5}$ and the purchase of rice insurance in column (1) were significantly negative at the 5% level, indicating that rice insurance

significantly reduced the positive effects of haze on pesticide application amounts. According to Figure 6, the marginal effect of haze on pesticide application amounts was 0.086 for rice farmers without rice insurance, but 0.068 for rice farmers with rice insurance. The reason for this may be that, after purchasing rice insurance, rice farmers could obtain compensation for the effects of diseases, insect pests, or natural disasters during rice planting, helping rice farmers to reduce risks and indirectly regulating the application of pesticides (Chi et al., 2019). However, the coefficients for the interaction term of $PM_{2.5}$ and rice insurance in column (4) were significantly positive at the 1% level, indicating that agricultural insurance significantly strengthened the positive effects of haze on pesticide fees. Figure 7 shows that the marginal effect of haze on pesticide fees was 0.022 for rice farmers without insurance, but 0.025 for insured rice farmers, probably because agricultural insurance weakens the risk awareness of rice farmers and encourages them to spend money on new pesticides to control pests.

Second, the coefficients for the interaction term of $PM_{2.5}$ and experience in columns (2) and (5) were both significantly negative at the 5% and 1% levels respectively, indicating that rice planting experience significantly reduced the positive effects of haze on pesticide application amounts and pesticide fees. Figures 8 and 9 both show the moderating effect of rice farmers' rice planting experience on pesticide application amounts and pesticide fees. For farmers with only five years of rice planting experience, the positive effects of haze on pesticide application amounts and pesticide fees were reduced by 9.34% and 3.12%, respectively, for every 1% increase in rice planting experience. However, for farmers with nearly 45 years of rice planting experience, the positive effects of haze on pesticide application amounts and pesticide fees reduced by only 6.69% and 1.69%, respectively, for every 1% increase in rice planting experience. Experienced rice farmers

who had been growing rice crops for a long time applied pesticides appropriately to control disease and improve the rice yield. Experienced rice farmers were usually more cautious about applying pesticides; hence, even in haze conditions, they strictly controlled the use of pesticides.

Third, the estimated coefficients of the interaction terms of $PM_{2.5}$ and the logarithm of rice planting scale in columns (3) and (6) were significantly positive at the levels of 5% and 1%, respectively, indicating that rice planting scale significantly strengthened the positive effects of haze on pesticide application amounts and pesticide fees. Figures 10 and 11 both show the moderating effect of rice planting scale on pesticide application amounts and pesticide fees. When the logarithm of rice planting equaled 1, the positive effects of haze on pesticide application amounts and pesticide fees increased by 7.61% and 2.21%, respectively, for every 1% increase in rice planting scale. When the logarithm of planting scale equaled 8, the positive effects of haze on pesticide application amounts and pesticide fees increased by 10.85% and 3.74%, respectively, for every 1% increase of rice planting scale. This was potentially attributable to the larger scale of rice cultivation making rice farmers pay greater attention to the benefits of rice cultivation and more willing to use pesticides to quickly eliminate pests. Also, haze increases air humidity by affecting rice photosynthesis, respiration, and transpiration, which provides favorable conditions for plant diseases and insect pests, such as aphids and rust, to proliferate. The larger the rice planting scale, the greater the risk of frequent rice crop pests and diseases, so to a certain extent, the interaction term strengthened the positive effects of haze on pesticide application.

Table 5

The effects of haze on pesticide application and pesticide fee after the introduction of interactive terms

Variable	Pesticide			Pesticide fee		
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.086***	0.093***	0.071***	0.022***	0.031***	0.020***
	(0.016)	(0.015)	(0.015)	(0.002)	(0.002)	(0.002)
$PM_{2.5}$×Insurance	-0.018**			0.003***		
	(0.007)			(0.001)		
$PM_{2.5}$×Experience		-0.001**			-0.001***	
		(0.000)			(0.000)	
$PM_{2.5}$×Lnarea			0.005**			0.002***
			(0.002)			(0.000)
Gender	-0.040	-0.047	-0.044	0.037***	0.032***	0.034***
	(0.089)	(0.089)	(0.089)	(0.018)	(0.018)	(0.018)
Age	-0.017***	-0.018***	-0.018***	-0.003***	-0.004***	-0.003***
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Edu2	-0.616	-0.568	-0.589	-0.012	-0.001	-0.013***
	(0.405)	(0.404)	(0.405)	(0.063)	(0.062)	(0.063)
Edu3	-0.704*	-0.656	-0.683*	-0.032	-0.021	-0.036
	(0.412)	(0.411)	(0.414)	(0.062)	(0.061)	(0.062)
Edu4	-0.723*	-0.663	-0.678	-0.008	0.001	-0.007
	(0.413)	(0.412)	(0.413)	(0.061)	(0.061)	(0.061)
Health	-0.064	-0.046	-0.049	-0.130	-0.128	-0.130
	(0.145)	(0.149)	(0.149)	(0.088)	(0.088)	(0.088)
Experience	0.008*	0.029***	0.009*	0.000	0.011***	-0.000
	(0.005)	(0.010)	(0.005)	(0.001)	(0.002)	(0.001)
Training	-0.337***	-0.333***	-0.314***	-0.148***	-0.145***	-0.149
	(0.087)	(0.088)	(0.088)	(0.020)	(0.020)	(0.020)
Preference	-0.637***	-0.672***	-0.676***	-0.129***	-0.121***	-0.123***
	(0.122)	(0.121)	(0.121)	(0.021)	(0.021)	(0.021)
Insurance	0.263	-0.376***	-0.383***	-0.227***	-0.104***	-0.107***
	(0.234)	(0.110)	(0.110)	(0.035)	(0.017)	(0.017)
Lnincome	-0.263***	-0.289***	-0.298***	-0.041***	-0.037***	-0.041***
	(0.055)	(0.055)	(0.057)	(0.010)	(0.010)	(0.010)
Rentin	0.123	0.093	0.0.91	0.045***	0.043***	0.042***
	(0.110)	(0.112)	(0.113)	(0.015)	(0.015)	(0.015)
Hhsize	0.063***	0.056***	0.059***	0.014***	0.013***	0.015***
	(0.021)	(0.021)	(0.021)	(0.004)	(0.004)	(0.004)
Rlabour	-0.056	-0.061*	-0.058*	-0.035***	-0.039***	-0.037***
	(0.035)	(0.036)	(0.035)	(0.008)	(0.008)	(0.008)
Lnarea	0.010**	0.132***	-0.018	0.051***	0.050***	-0.021*
	(0.042)	(0.046)	(0.072)	(0.007)	(0.007)	(0.012)
Membership	0.196**	0.152*	0.130	0.011	0.010	0.000

	(0.079)	(0.078)	(0.083)	(0.015)	(0.015)	(0.015)
Vtechinician	-0.129	-0.104	-0.096	-0.030**	-0.027*	-0.024*
	(0.116)	(0.115)	(0.112)	(0.015)	(0.014)	(0.015)
Topography	1.186***	1.301***	1.338***	-0.290***	0.258***	0.276***
	(0.216)	(0.231)	(0.230)	(0.030)	(0.030)	(0.030)
Regional fixed effect	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES
Residual	-0.063***	-0.069***	-0.074***	-0.024***	-0.023***	-0.025***
	(0.014)	(0.014)	(0.015)	(0.002)	(0.002)	(0.002)
Constant	3.081***	3.055***	3.877***	0.629**	0.307*	0.726***
	(0.707)	(0.675)	(0.726)	(0.164)	(0.158)	(0.164)
Observations	4908	4908	4908	4908	4908	4908
R-squared	0.034	0.033	0.033	0.069	0.077	0.074

Notes: The standard errors of CF approach are obtained through repeated sampling of bootstrap for 1,000 times, and they are in the parentheses.

*Significant at 10% level,**Significant at 5% level,*** Significant at 1% level.

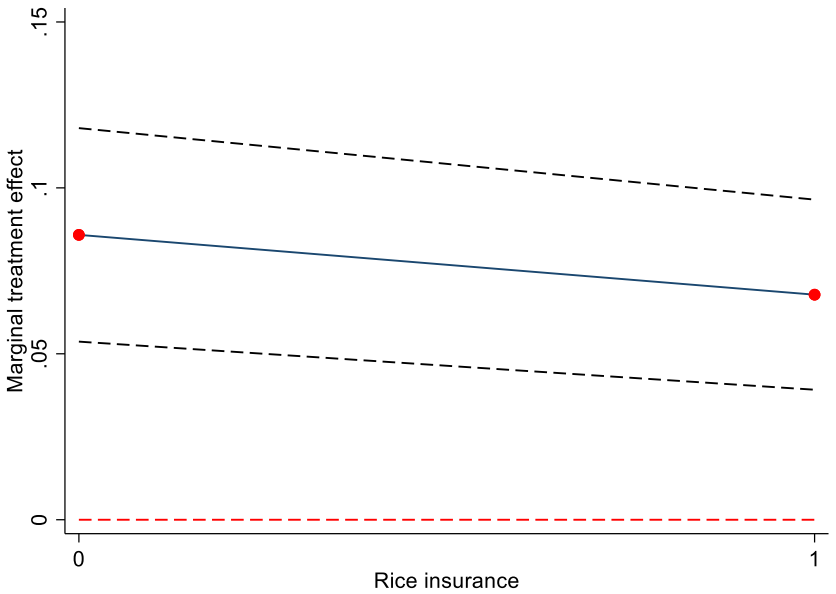

Fig.6 Moderating effect of rice insurance on pesticide dosage per mu

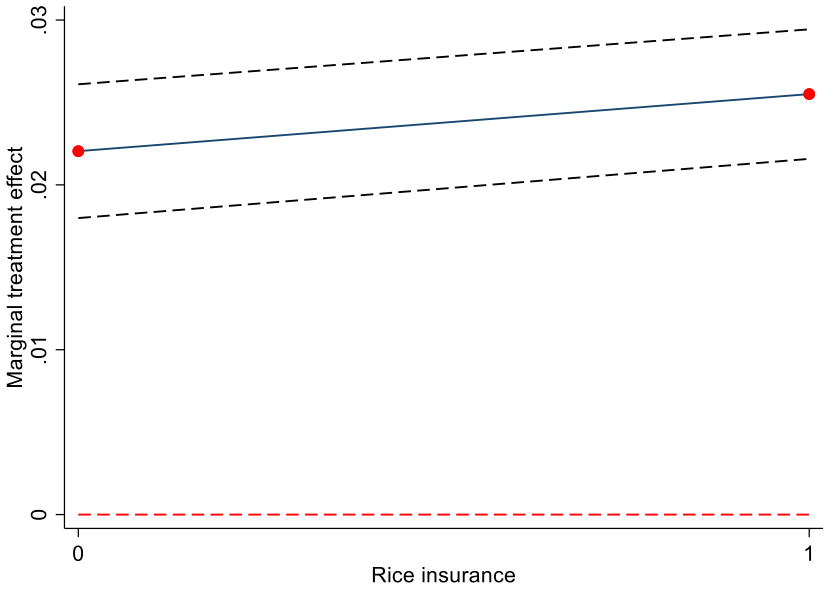

Fig.7 Moderating effect of rice insurance on pesticide fee per mu

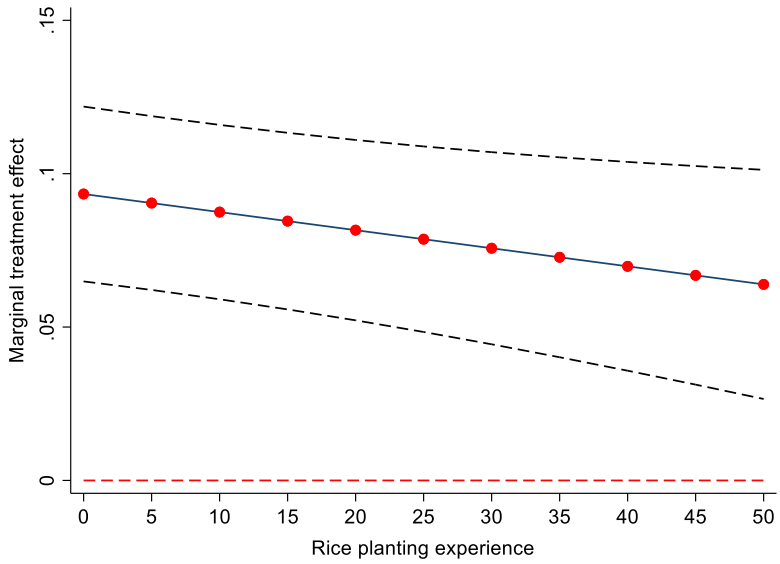

Fig.8 Moderating effect of rice planting experience on pesticide dosage per mu

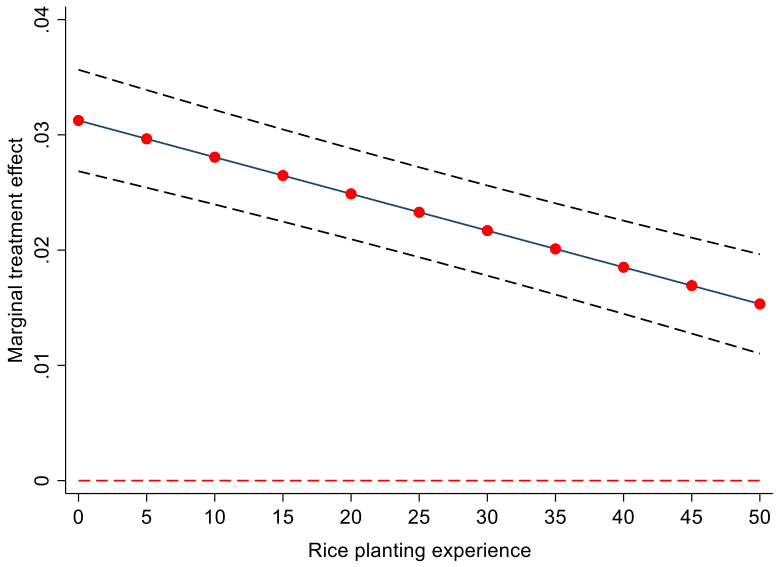

Fig.9 Moderating effect of rice planting experience on pesticide fee per mu

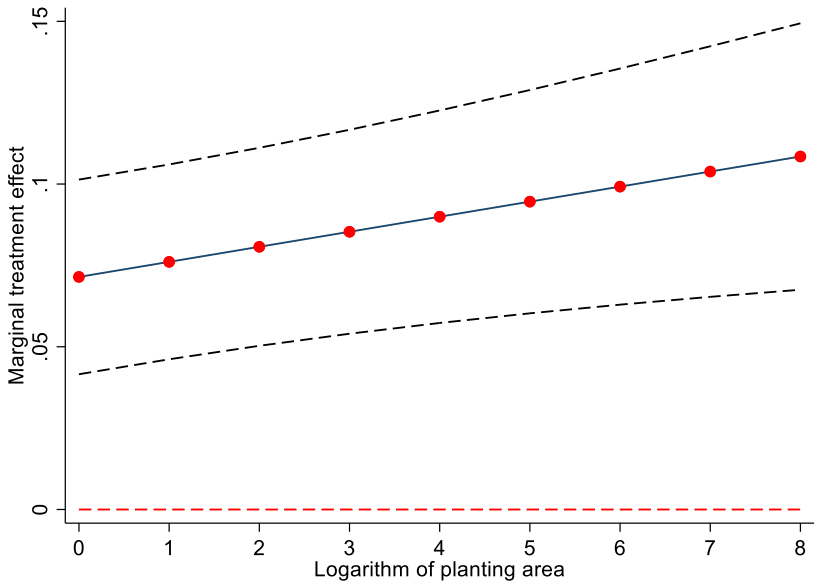

Fig.10 Moderating effect of rice planting scale on pesticide dosage per mu

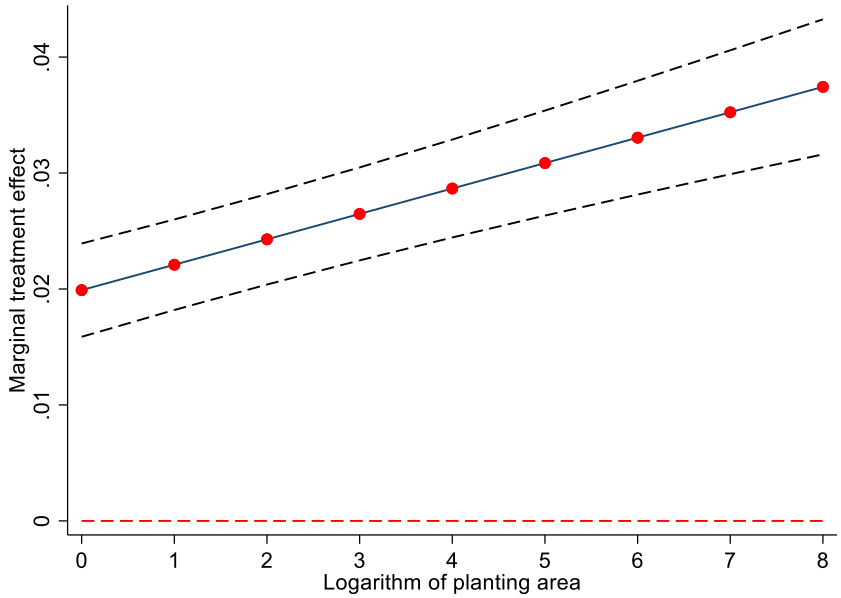

Fig.11 Moderating effect of rice planting scale on pesticide fee per mu

5.4. Robustness test

Construction of IV Bounds. In Section 3, we mentioned that the instrumental variable "air flow strength" was only an approximately perfect instrumental variable, requiring the use of the UCI and LTZ methods to test the robustness of the CF regression results. Table 6 shows the estimated results obtained by using these two methods. It is worth noting that, when we used the UCI method in the case of both $\omega_0 \in [0,0]$ or $\omega_0 \in [0,1]$, the lower bound of the β value of the effects of $PM_{2.5}$ on pesticide application amounts was 0.048, and the lower bound of the β value of the effects of $PM_{2.5}$ on pesticide fees was 0.019. The upper bound of the β value varied with intervals of ω_0. The upper bound of the β value of the effects of $PM_{2.5}$ on pesticide application amounts was 0.111 when $\omega_0 \in [0, 0]$, and the upper bound of the β value of the effects of $PM_{2.5}$ on pesticide application amounts was 0.214 when $\omega_0 \in [0, 1]$, indicating that the closer ω_0 was to 0, the more accurate the β value was. Similarly, the upper bound of the β value of the effects of PM2.5 on pesticide fees was more accurate when $\omega_0 \in [0, 0]$ than when $\omega_0 \in [0, 1]$.

Table 6

The estimated results of UCI and LTZ

Variable	Pesticide dosage			Pesticide fee		
	UCI		LTZ	UCI		LTZ
	Lower Bound	Upper Bound		Lower Bound	Upper Bound	
$PM_{2.5}(\omega_0 \in [0, 0])$	0.048	0.111	0.089***	0.019	0.028	0.033***
$PM_{2.5}(\omega_0 \in [0, 1])$	0.048	0.214	(0.019)	0.019	0.137	(0.010)
Control variables	YES	YES	YES	YES	YES	YES
Observation	4908	4908	4908	4908	4908	4908

Notes: *Significant at 10% level,**Significant at 5% level,*** Significant at 1% level.

The value of the coefficient β of haze affecting pesticide application amounts, obtained by using the LTZ method, was significantly 0.089 at the 1% level, and the value of the coefficient β of haze affecting pesticide fees was significantly 0.033 at the 1% level. Also, based on the prior value of ω indexed by parameter δ, we combined Figures 12 and 13 to observe the estimated results of the LTZ method. The dotted lines in Figures 12 and 13, respectively, represent the confidence intervals of pesticide application amounts and pesticide fees for rice farmers when the confidence degree was 95%, and the solid lines in the center, respectively, represent the point estimation results for parameter β corresponding to different δ values. When δ = 0, the confidence interval for the pesticide application amounts of rice farmers was [0.05, 0.11] and the confidence interval for the pesticide fees was [0.02, 0.035]. When δ = 0.5, the confidence interval for pesticide application amounts was [0.045, 0.21], and the confidence interval for pesticide fees was [-0.01, 0.15]. The above results suggested that the closer the δ value was to 0, the more accurate the β value was.

Although the results obtained using the UCI and LTZ methods to estimate approximately perfect instrumental variables were not exactly the same as those obtained by estimating the perfect instrumental variables, it was true that haze had a positive effect on the pesticide use behavior of rice farmers; therefore, it was reasonable to select the air flow strength as the instrumental variable for the CF regression.

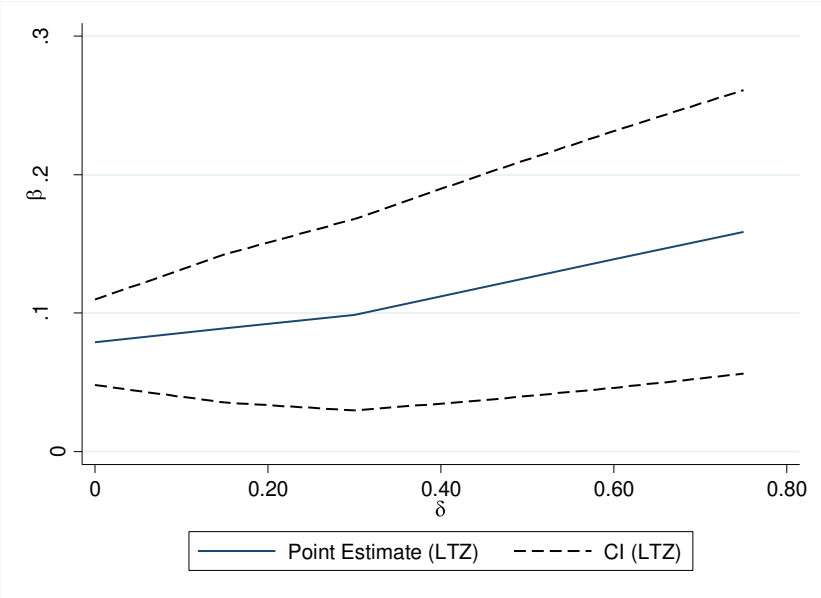

Fig.12 The effects of haze on pesticide dosage per mu

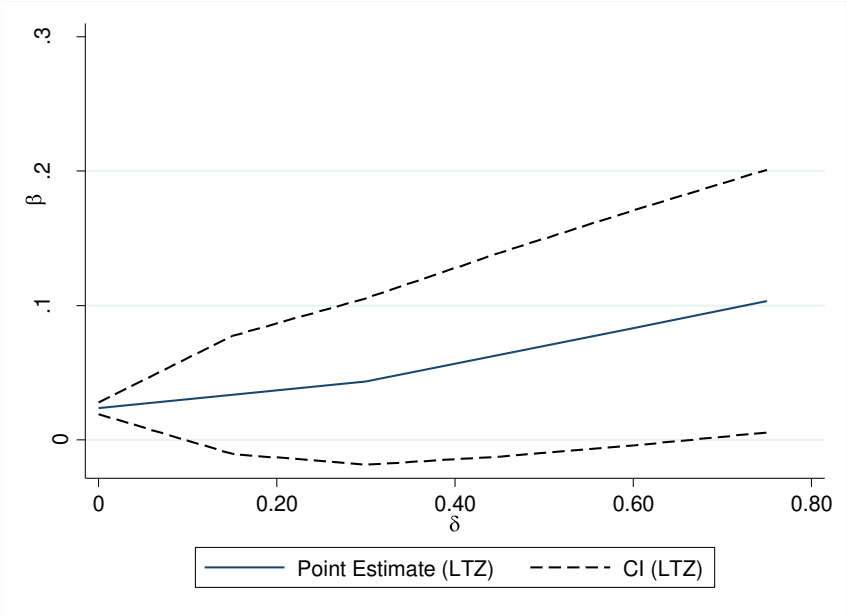

Fig.13 The effects of haze on pesticide fee per mu

Heteroscedasticity-based Identification Strategy: Table 7 shows the estimated results of the heteroscedasticity identification method. Columns (1) and (3), report Lewbel estimates with higher-moment internal instruments respectively. The Breusch–Pagan test results in Table 8 were significant at the 1% level, indicating that the equation error term for haze concentration on the pesticide application behavior of rice farmers in the regression equation was heteroskedastic. Thus

547 satisfying the third condition for the Lewbel approach. Also, the overidentification test based on the
548 Hansen J statistic fails to reject the null hypothesis that all instruments are valid. Thus, we have
549 some confidence in the overall set of instruments used in the Lewbel estimation. Similar key
550 indicators and results are reported in column(2) and (4) for the IV+Lewbel estimation. The
551 coefficient of $PM_{2.5}$ was significantly positive at the level of 1% in all four models, which was
552 consistent with the previous estimates.

553 **Table 7**

554 Estimation results based on heteroscedasticity identification

Variable	Pesticide dosage		Pesticide fee	
	(1)	(2)	(3)	(4)
	Lewbel	IV+Lewbel	Lewbel	IV+Lewbel
$PM_{2.5}$	0.037*	0.068***	0.026***	0.024***
	(0.020)	(0.011)	(0.004)	(0.002)
Control variable	YES	YES	YES	YES
Regional fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
Constant	0.135	-0.924**	-0.292*	-0.210***
	(0.675)	(0.369)	(0.149)	(0.066)
Observations	4,908	4,908	4,908	4,908
Cragg-Donald Wald F statistic	42.016***	1096.05***	42.016***	112.423***
Breusch-Pagan test	2437.81***	2437.81***	2437.81***	2437.81***
Hansen J statistic (p-value)	0.1211	0.1372	0.2336	0.2804
Endogeneity test	1.025	32.137***	61.055***	167.733***
R-squared	0.019	0.019	0.264	0.203

555 *Notes:* *Significant at 10% level,**Significant at 5% level,*** Significant at 1% level.
556

557 **6. Conclusions and policy implications**

558 This study estimated the effects of haze concentration ($PM_{2.5}$) on the use of pesticides by rice
559 farmers in China using nationally representative five-wave farm-household annual survey data from
560 2014 to 2018. We employed a CF approach to calculate the local average treatment effect of haze
561 concentration. Overall, we found that haze had a significant and positive impact on the use of
562 pesticides by rice farmers; more precisely, a 1% percent increase in $PM_{2.5}$ increased the amount of

563 pesticide applied by 7.9 percentage points and the pesticide fees by 2.3 percentage points.
564 Furthermore, we conducted additional tests to address potential endogeneity issues and found that
565 our results were robust for different estimation techniques, including the omitted variable bias test,
566 the IV bounds construction, and the heteroscedasticity identification.

567 We then studied the heterogeneous effects across different characteristics of rice farmers. We
568 found the effects of haze concentration increases on pesticide dosages to be stronger for rice farmers
569 without rice insurance, while the effect of haze concentration increases on pesticide fees was
570 stronger for rice farmers with rice insurance. We also found the effects of haze concentration
571 increases on the use of pesticides, including pesticide dosages and fees, to be weaker for rice farmers
572 with strong rice-planting experience and those with small-scale rice planting.

573 The results of this study have profound policy implications. The extent of haze concentration
574 is an important factor causing an increase in the use of pesticides by farmers; therefore, the
575 government should focus on reducing air pollution, and the aim of public policy should be to
576 increase pollution-control resources. Furthermore, our results showed that agricultural insurance as
577 a formal risk compensation mechanism encouraged farmers to reduce pesticide dosages in response
578 to increases in haze concentration. This further indicated that smallholders in developing countries
579 are risk averse when they have no formal risk compensation mechanisms; therefore, they tend to
580 use more pesticides when haze becomes more severe. Simultaneously, the government should
581 establish mechanisms for reducing agricultural losses, such as an agricultural insurance system, and
582 guide and encourage smallholders to purchase agricultural insurance.

583 Our results also showed that the rice-planting experience of household heads weakened the
584 positive effect of haze concentrations on the use of pesticides. According to this conclusion,

government departments should establish effective incentive schemes to encourage farmers with significant rice-planting experience to share their experience of pesticide use and positively influence social norms. Also, according to our results, when the haze becomes worse, the government should pay more attention to farmers with large-scale planting areas. Since farmers with large-scale planting areas pay more attention to high yields and increasing their income from the land (Liu et al., 2018), they tend to use more pesticides to manage the increased pest populations caused by serious haze pollution. The government should therefore (1) formulate rules to regulate the use of pesticides by farmers with large-scale planting areas, (2) enhance the ability of farmers to cope with agricultural output losses caused by haze pollution, such as through pest control training, (3) improve the market mechanisms, and (4) guide farmers to adopt green production technology.

Ethics approval and consent to participate

The experimental protocol was established, according to the ethical guidelines of the Helsinki Declaration, and was approved by the Human Ethics Committee of Sichuan Agricultural University. Written informed consent was obtained from individual or guardian participants.

Consent for publication

The work described has not been published before (except in the form of an abstract or as part of a published lecture, review, or thesis); it is not under consideration for publication elsewhere; its publication has been approved by all co-authors, if any; its publication has been approved (tacitly or explicitly) by the responsible authorities at the institution where the work is carried out.

Authors Contributions

Lili Guo: Conceptualization, Methodology, Writing-Original draft preparation, Reviewing and Editing; Andi Cao: Methodology, Writing- Reviewing and Editing; Minjun Huang: Visualization, Conceptualization, Methodology; Houjian Li: Supervision, Investigation, Data Collection,

Methodology, Software, Reviewing and Editing.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The authors do not have permission to share data.

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Figures

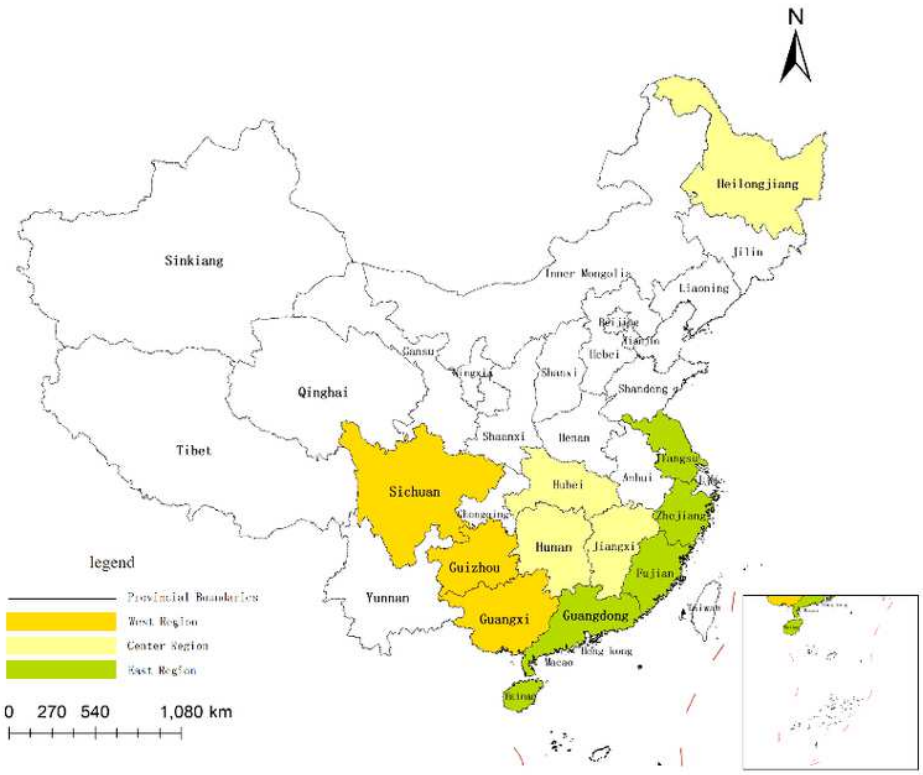

Figure 1

The distribution of selected rice production areas in China Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

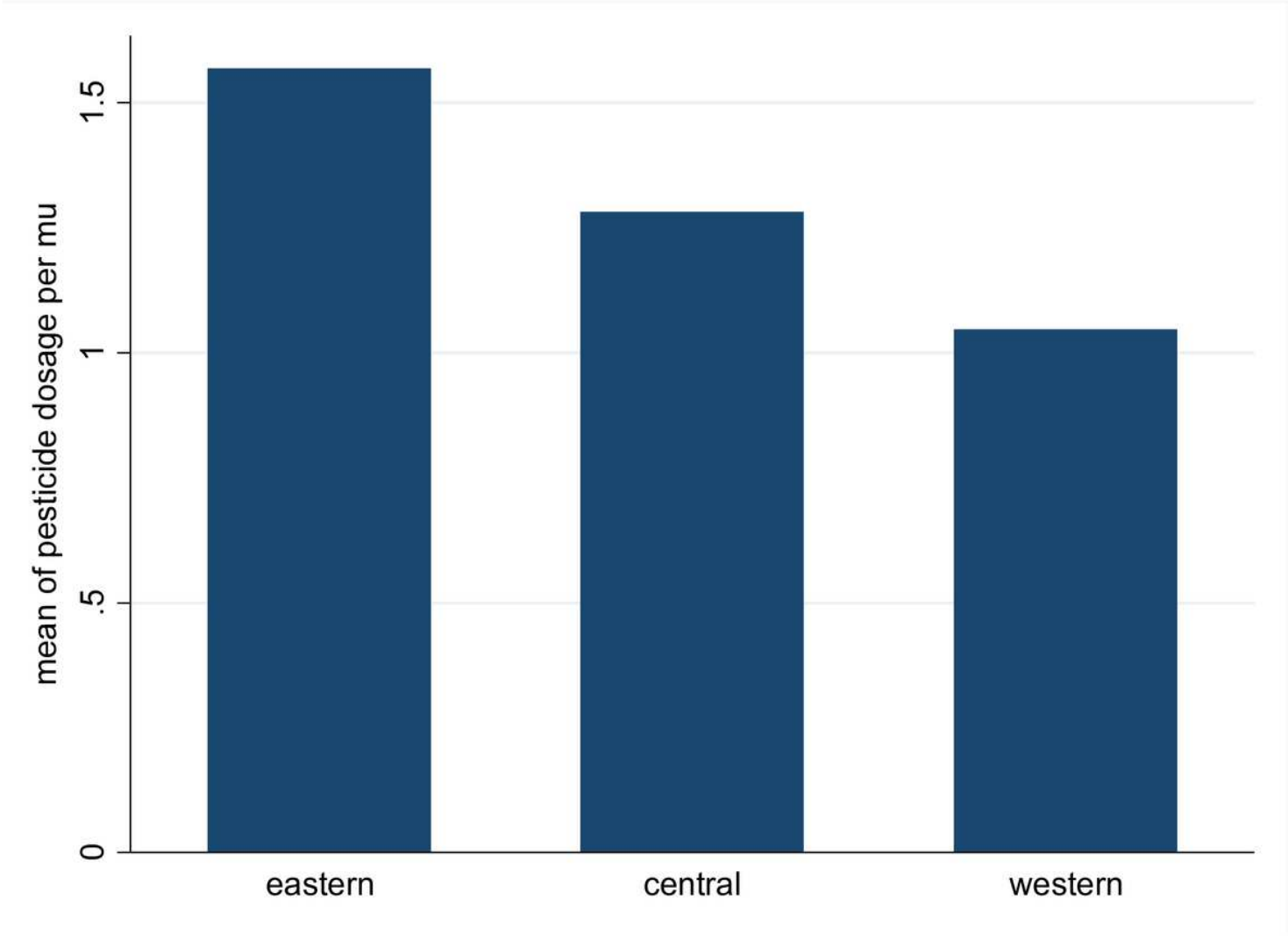

Figure 2

The mean of pesticide dosage per mu in three regions

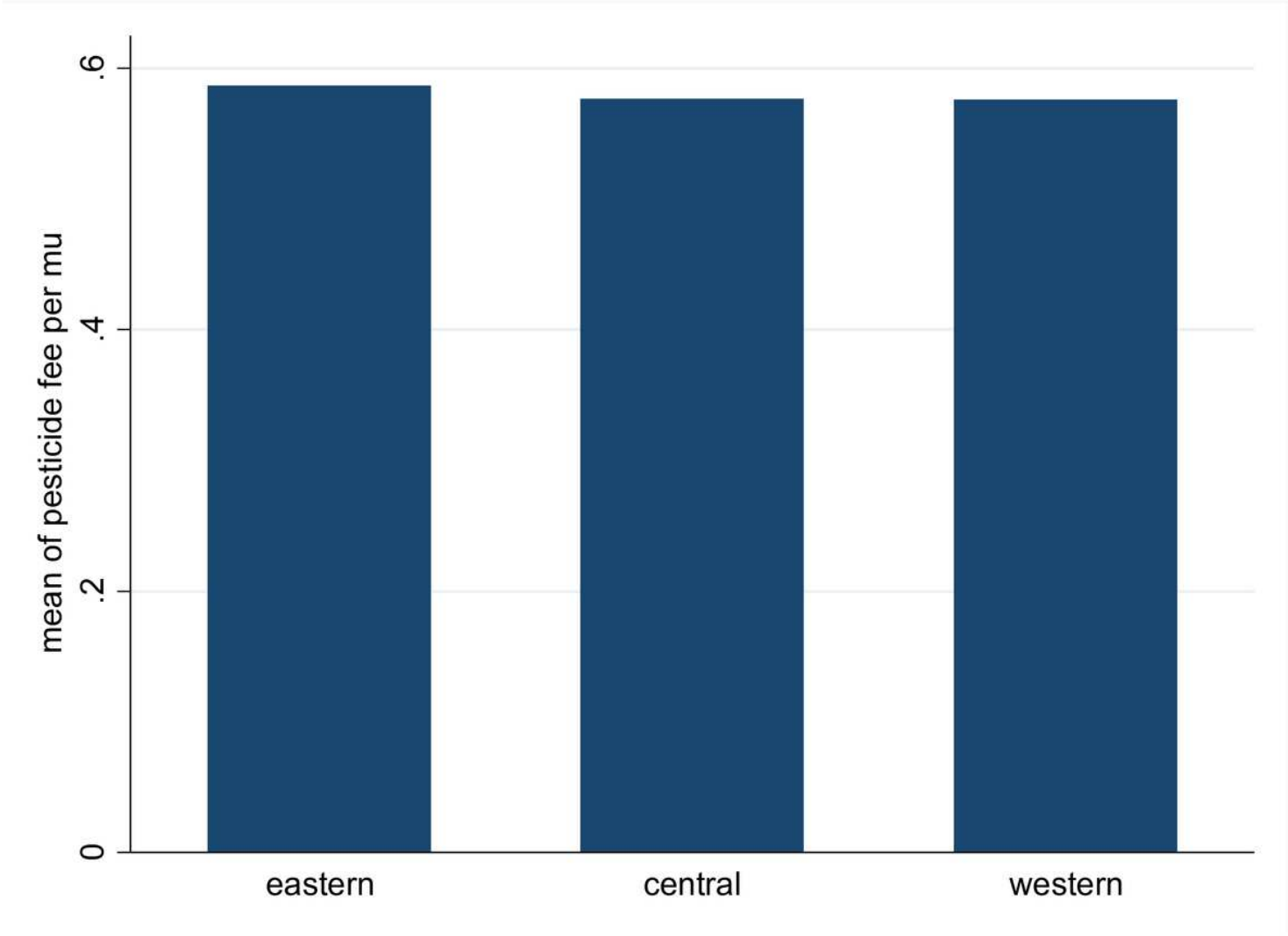

Figure 3

The mean of pesticide fee per mu in three regions

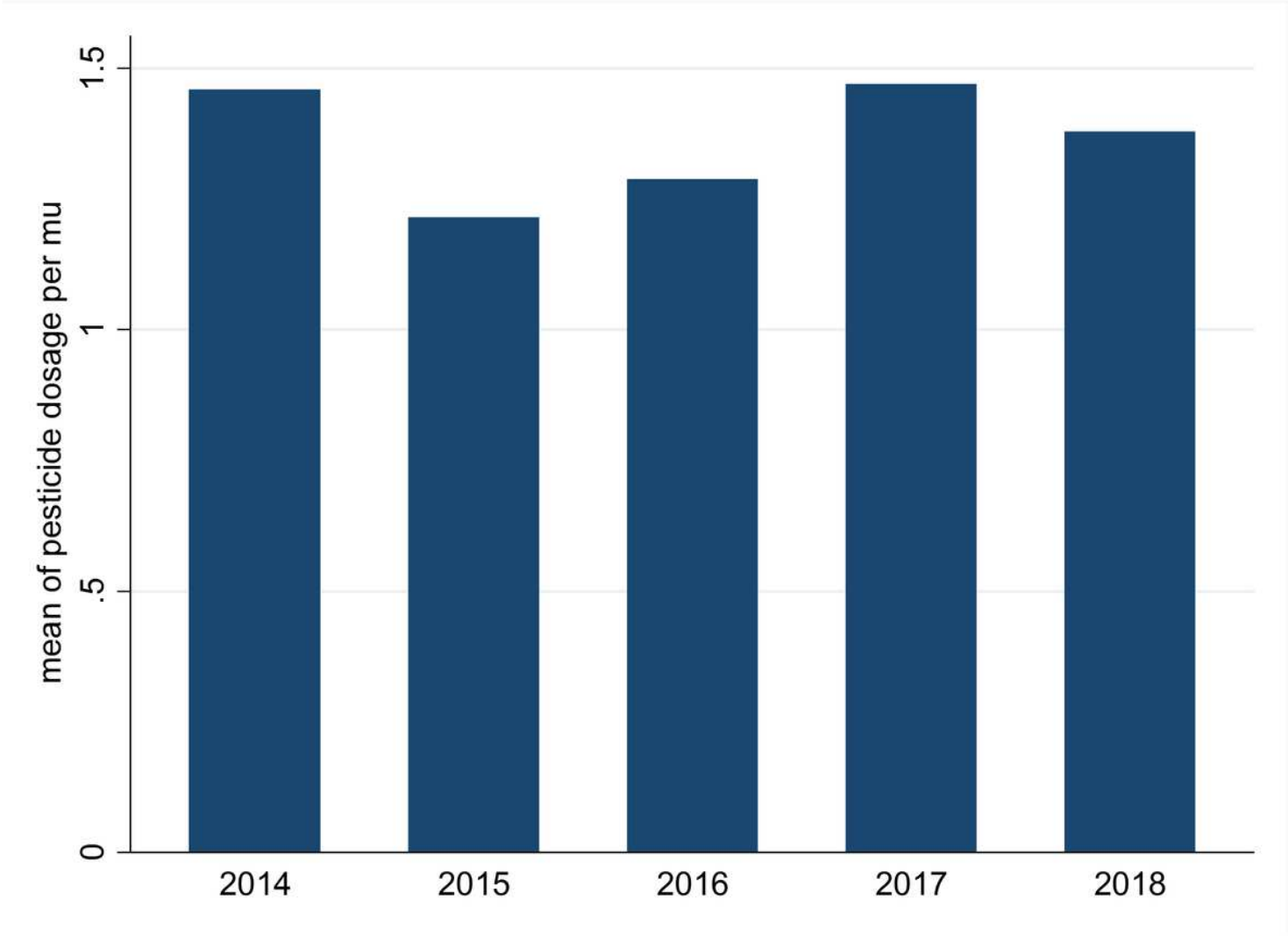

Figure 4

The mean of pesticide dosage per mu during 2014-2018

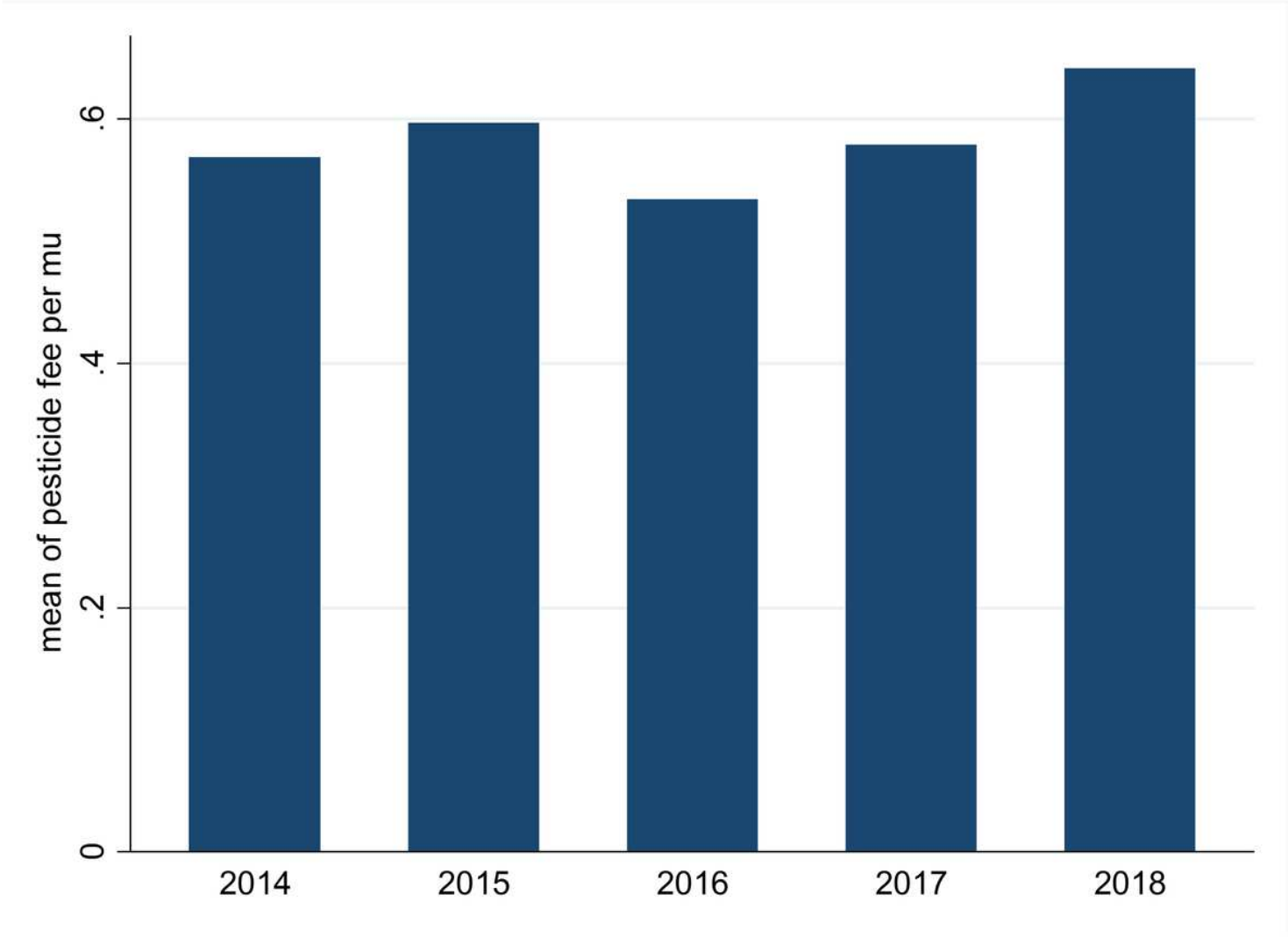

Figure 5

The mean of pesticide fee per mu during 2014-2018

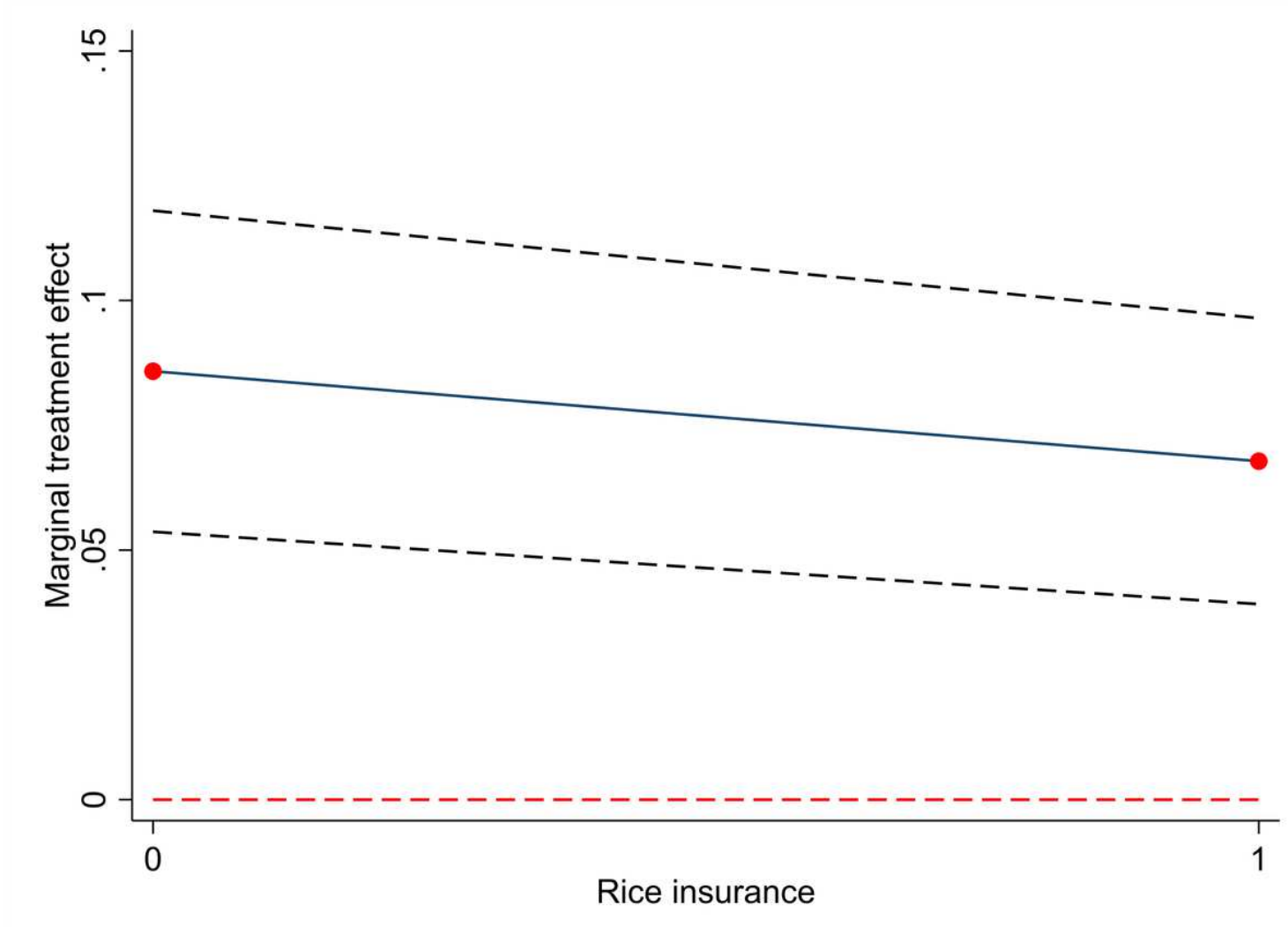

Figure 6

Moderating effect of rice insurance on pesticide dosage per mu

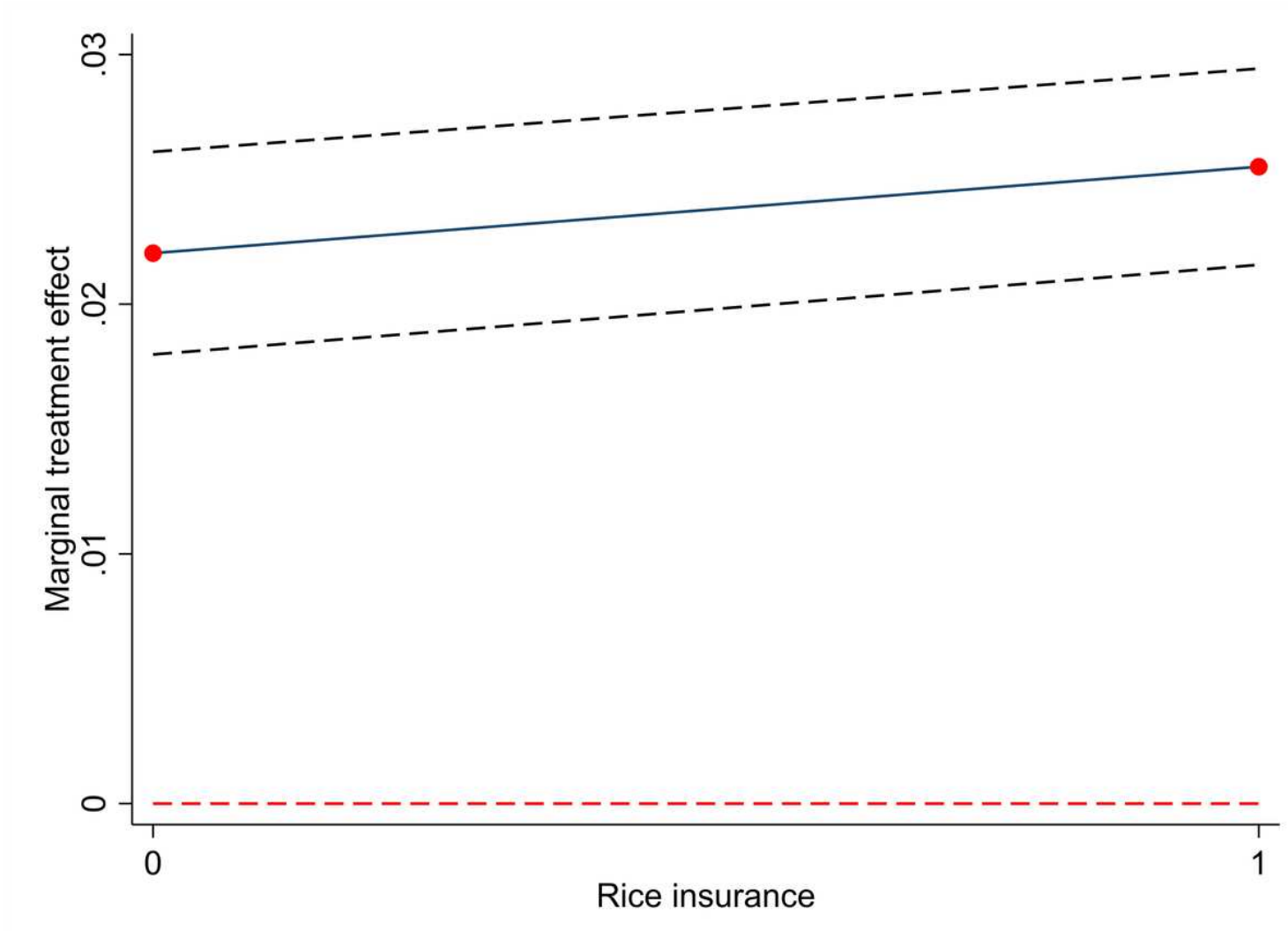

Figure 7

Moderating effect of rice insurance on pesticide fee per mu

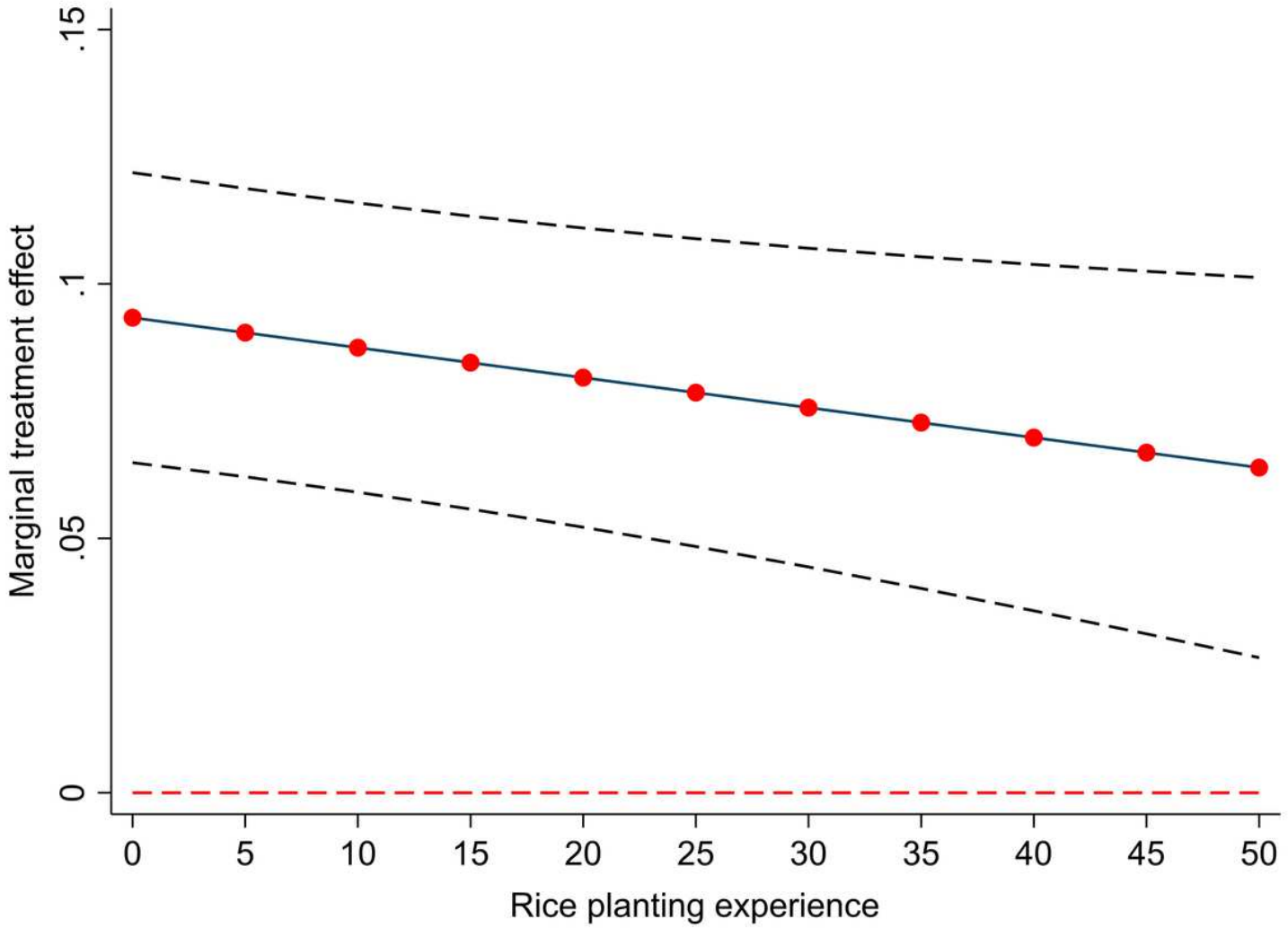

Figure 8

Moderating effect of rice planting experience on pesticide dosage per mu

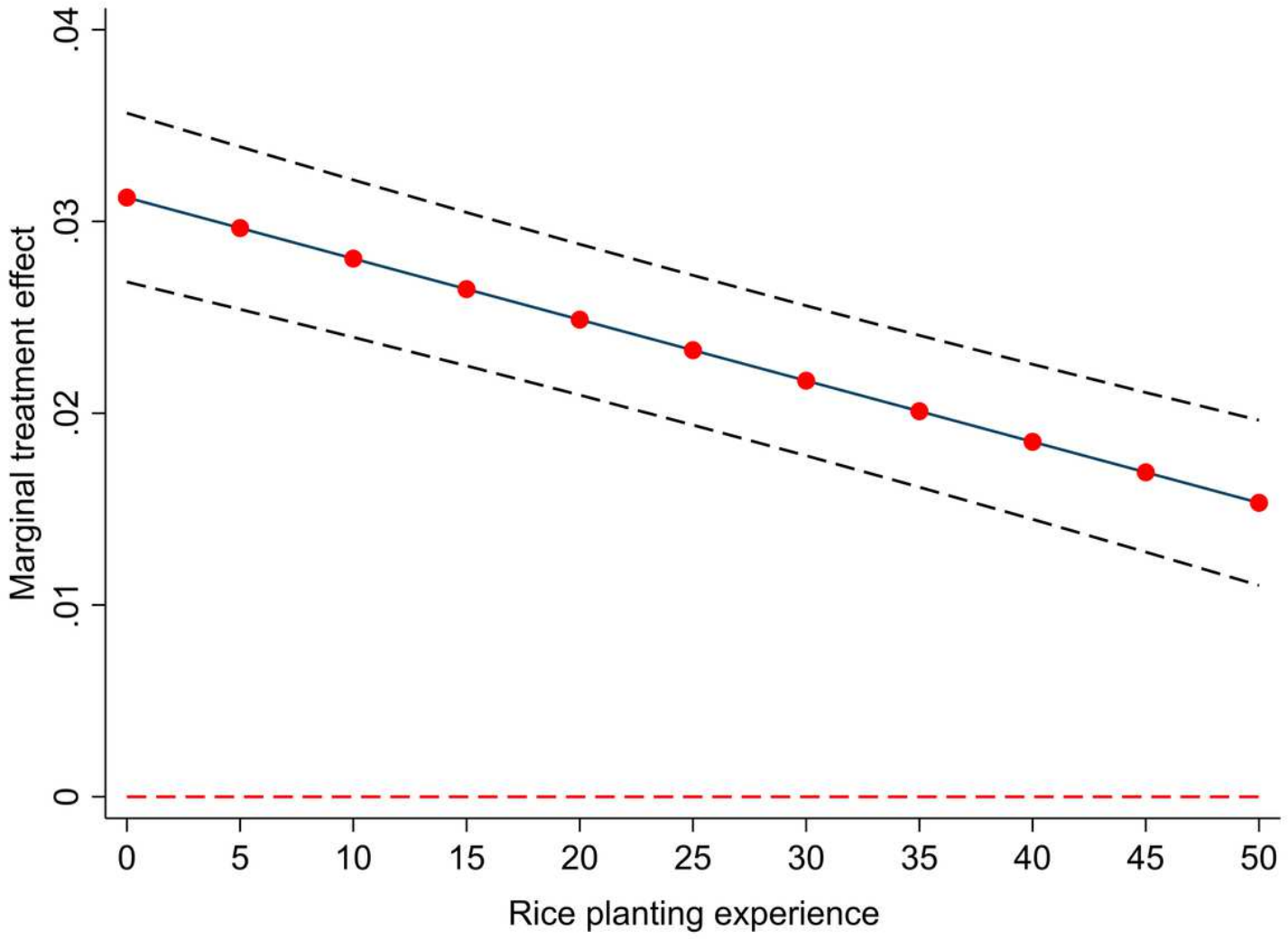

Figure 9

Moderating effect of rice planting experience on pesticide fee per mu

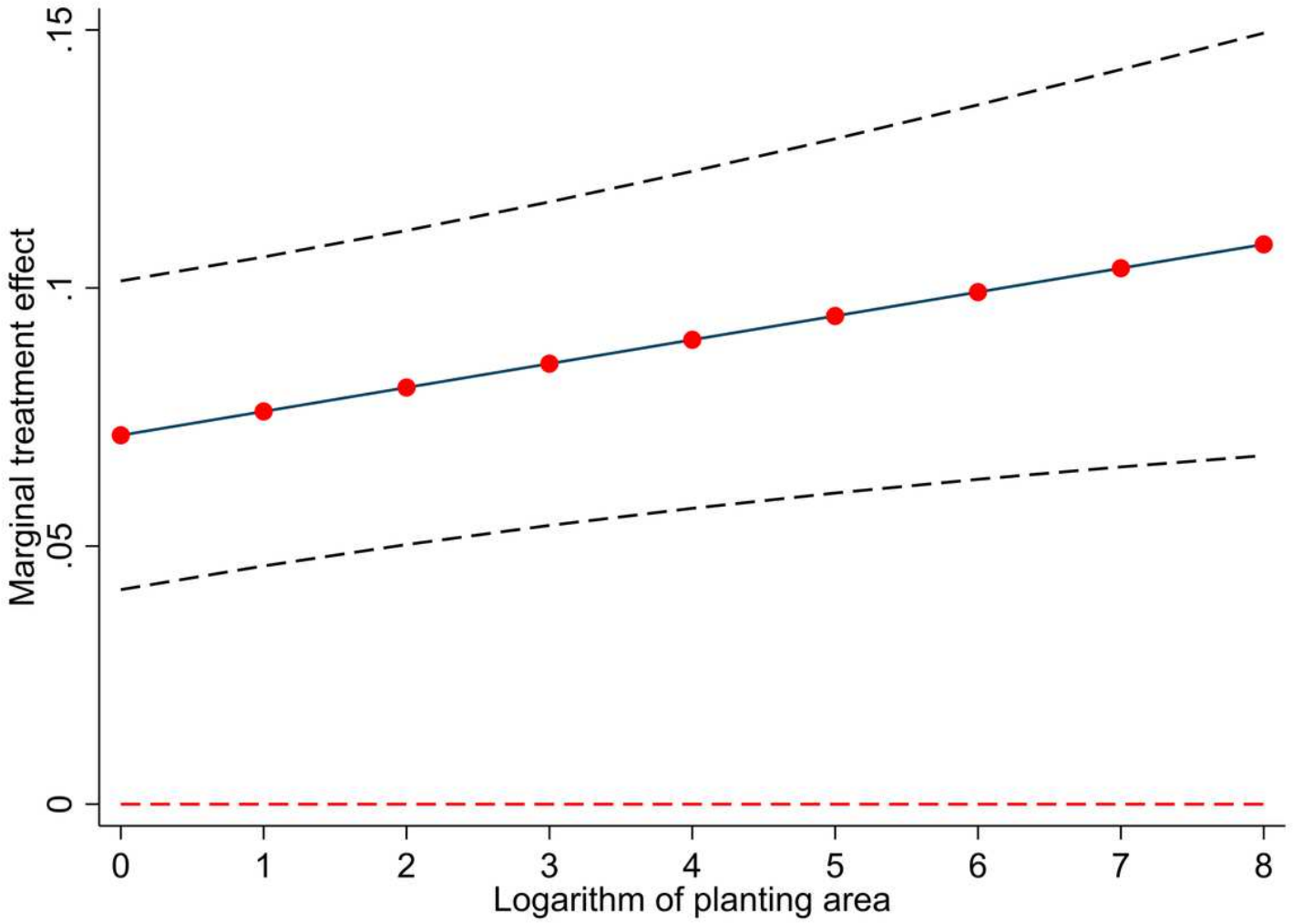

Figure 10

Moderating effect of rice planting scale on pesticide dosage per mu

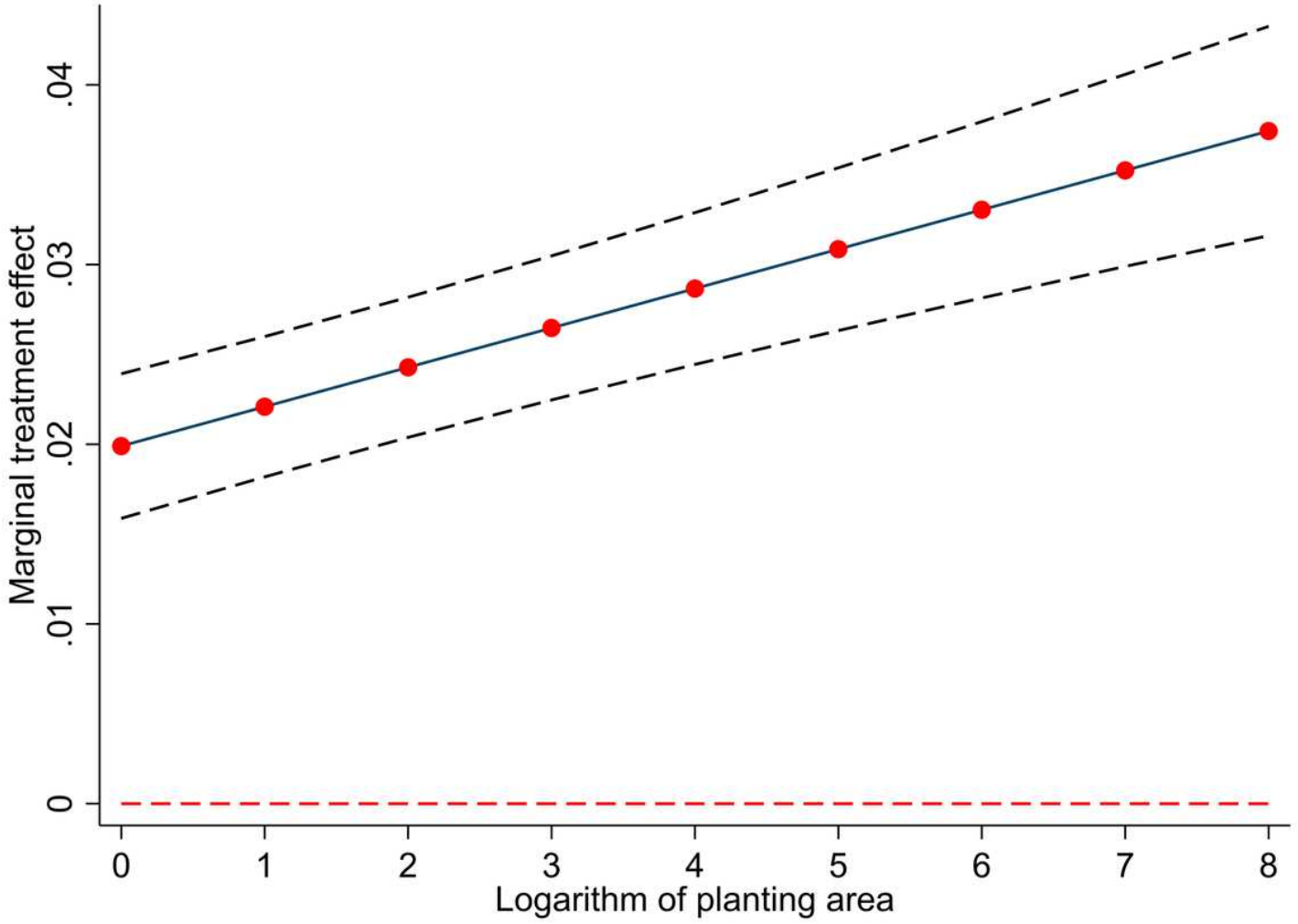

Figure 11

Moderating effect of rice planting scale on pesticide fee per mu

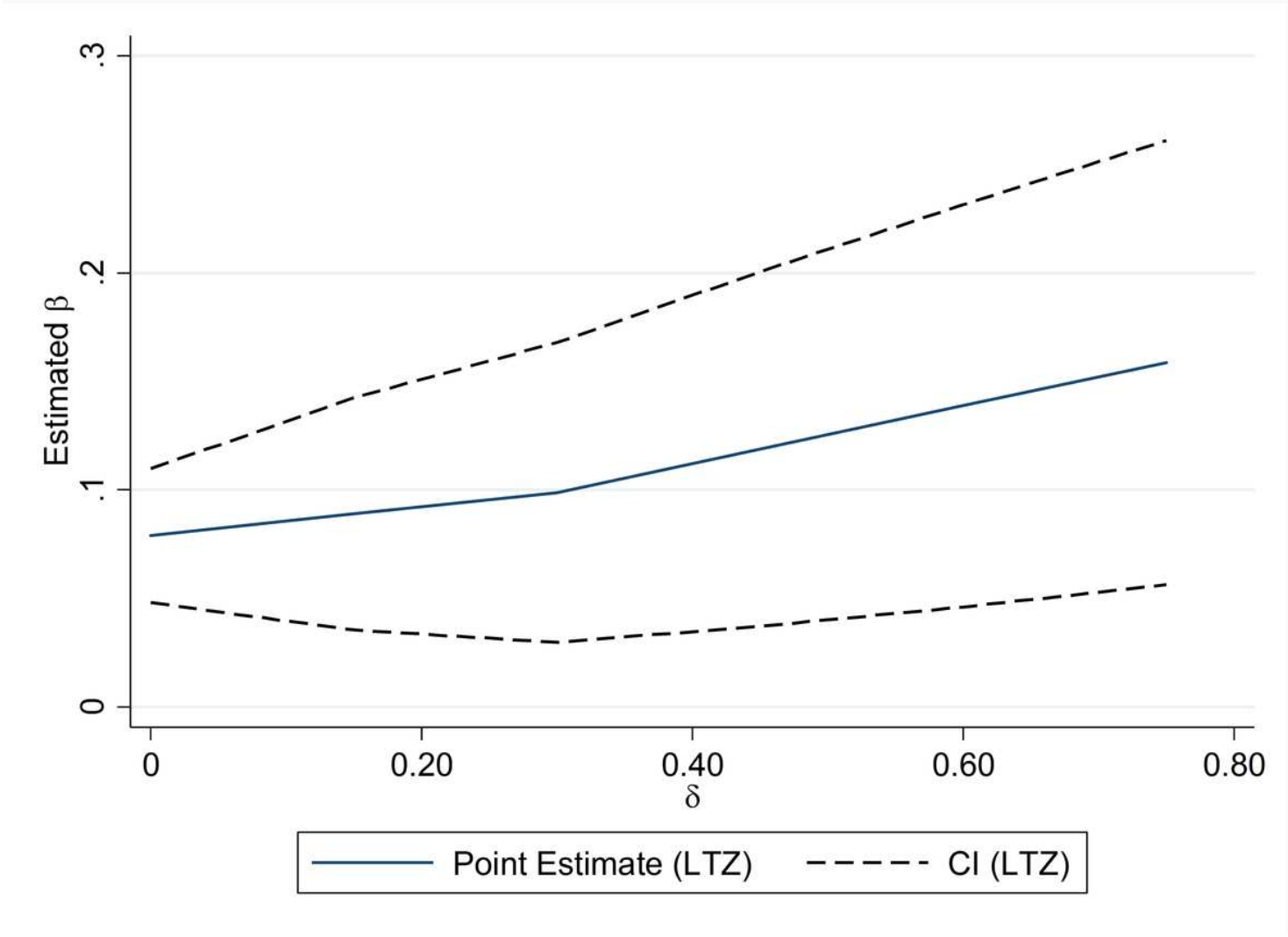

Figure 12

The effects of haze on pesticide dosage per mu

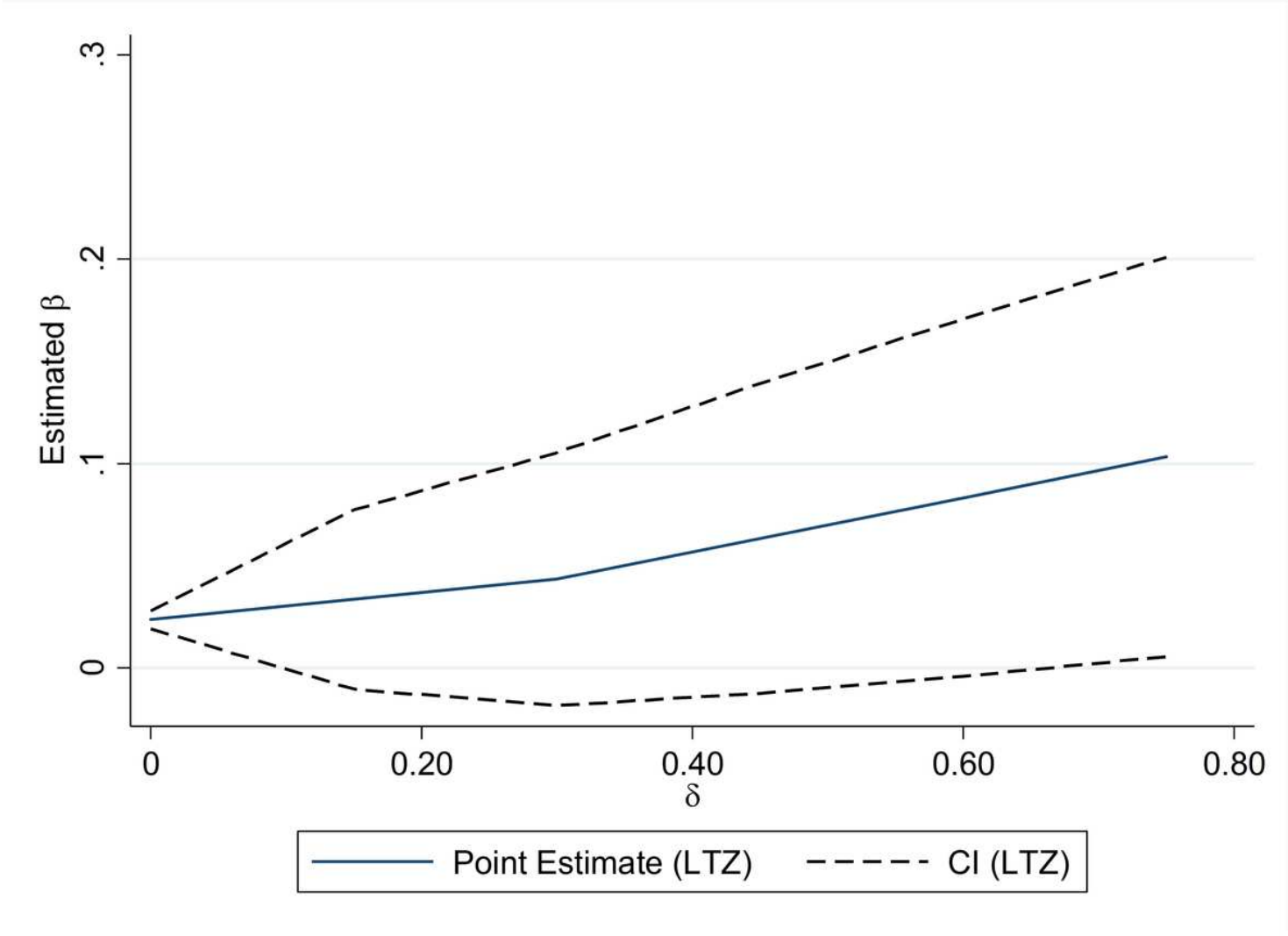

Figure 13

The effects of haze on pesticide fee per mu