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Do Pesticide Retailers' Recommendations Aggravate Pesticide Overuse? Evidence from Rural China

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Abstract: In rural China, pesticide retailers are often accused of recommending farmers apply more pesticides than the scientifically recommended rate, while playing an important role in providing technical information regarding pesticide use to farmers. However, there is little empirical evidence on the relationship between pesticide retailers' recommendations and farmers' pesticide overuse. Using survey data from 1084 rice farmers in four provinces, this study utilized an endogenous switching probit model to examine the impact of pesticide retailers' recommendations on the overuse of pesticides at the level of pest-control observation, accounting for potential self-selectivity bias. Results show that the proportion of pesticide overuse at the level of pest-control observation for controlling major pests, secondary pests, and weeds is 58.5, 55, and 40.6%, respectively. Pesticide retailers' recommendations are found to increase the probability of pesticide overuse at the level of pest-control observation for controlling major pests, secondary pests, and weeds by 62.1, 59.3, and 58.3%, respectively. The robustness check using a conditional mixed process model provided consistent findings. Accordingly, this study proposes that more efforts should be made to provide additional technology training activities for pesticide retailers, strengthen regulations on pesticide retailers' information recommendations, and further improve socialized agricultural technology services.

Keywords: pesticide use; information source; endogenous switching probit model; self-selectivity bias



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1. Introduction

The contribution of pesticides to agricultural production and food security has been widely recognized worldwide [1]. Estimates indicate that for each 10% increase in pesticide application, grain crop yield increases by nearly 1% in China [2]. As one of the largest pesticide consumers in the world, China has experienced a dramatic increase in pesticide application with the total quantity of pesticides used in agriculture rising from 144.5 thousand tons in 1990 to 262.7 thousand tons in 2020 [3]. Note that considerable evidence shows that China's farmers overuse pesticides in grain and cash crop production [4–6], which has been criticized for causing a series of adverse consequences, including agricultural nonpoint source pollution [7,8], negative health outcomes for farmers [9,10], food quality deterioration [11–13], and developing resistance in crop pests [14,15]. In 2015, China's Ministry of Agriculture and Rural Affairs launched Action Plans to Achieve Zero Growth of Chemical Pesticides to decrease the pesticide application rate [16].

Previous studies have discussed the determinants of pesticide overuse, mainly focusing on farmers' individual characteristics, farm size, risk preferences, and participation in technology training [17–20]. However, farmers in China have often been considered to lack professional knowledge of pest management and pesticide use [21], and thus, their

decisions regarding pesticide application highly depend on access to external information [8,22]. In pesticide application, the role of information in guiding farmers to use pesticides properly cannot be overemphasized. Farmers with poor knowledge would have difficulty selecting correct pesticides from a plethora of available products and applying pesticides in scientifically recommended dosages [23–25]. Because of information asymmetry between farmers and information providers [26], farmers' acquisition of inadequate information on pest management and pesticide use would lead to pesticide misuse and even overuse [12,24,25].

While the Chinese government has made great efforts to solve such information asymmetry and compel information providers to provide unbiased and correct information to farmers [27,28], these efforts have not been very effective. Thus, a large number of farmers rely on informal sources of information, such as pesticide retailers [29,30]. For instance, a farmer survey in 2016 found that 28.6% of 2293 farmers relied on pesticide retailers' recommendations, whereas 15% of farmers relied on agricultural extension agents in China [24,25]. Xu et al. [31] also reported that the proportion of farmers obtaining information from pesticide retailers was 7% higher than that of farmers obtaining information from agricultural extension agents. In contrast to pesticide retailers in other countries (e.g., European countries), pesticide retailers in China often have dual roles, namely pesticide sellers and information providers, and thus, they are important parts of the socialized agricultural technology service system [32]. In general, pesticide retailers in China often get their information regarding pesticide use from both the government departments and pesticide firms [29,33]. Meanwhile, pesticide retailers in China provide information regarding pesticide use to farmers in multiple ways. Li et al. [29,33] found that about one third of pesticide retailers in China formally organize technical training activities for farmers, but more frequently they provide information regarding pesticide use to farmers in informal ways when they sell pesticides at farmers' request.

However, the relationship between pesticide retailers' recommendations and farmers' pesticide use remains controversial. Several previous studies pointed out that pesticide retailers may mislead farmers to increase pesticide use, and even recommend banned and hazardous pesticides to farmers [29,30,33]. Jin and Bluemling [23] observed that pesticide retailers provide misleading information to farmers for higher commercial profits. Li et al. [33] found that farmers obtaining information from pesticide retailers increase their pesticide application rate by 20.5% compared with those obtaining information from agricultural extension agents. In contrast, several other studies held the opposite conclusions. For example, Alam and Wolff [34] reported that farmers obtaining information from pesticide retailers decrease the pesticide application rate. Pan et al. [8] similarly found that farmers obtaining information from pesticide retailers decrease the pesticide application rate by 18.5%. Chen et al. [35] also showed that pesticide retailers' recommendations contribute to a reduction in the frequency and rate of pesticide application.

Previous studies have laid a solid foundation for understanding the relationship between pesticide retailers' recommendations and farmers' pesticide use. Nonetheless, there is considerable room for improvement. First, although previous studies have investigated the effect of pesticide retailers' recommendations on the pesticide application rate, little evidence has been provided on whether pesticide retailers' recommendations affect farmer's pesticide overuse. A better understanding of the relationship between pesticide retailers' recommendations and pesticide overuse is constructive for regulating pesticide retailers' information provision regarding pesticide use. Second, much existing literature defines pesticide overuse as the scenario in which the value of the marginal product of pesticides is below the corresponding marginal cost [36]. However, farmers often apply multiple active ingredients of pesticides to control a certain target pest. The definition of pesticide overuse from a pure economic perspective cannot measure whether farmers overuse pesticides to control each pest. Third, previous studies have employed ordinary least squares and probit regression models to estimate the impact of pesticide retailers' recommendations on pesticide overuse [22], failing to account for observed and unobserved factors that

may simultaneously affect farmers' information acquisition from pesticide retailers and pesticide overuse, which might lead to self-selectivity bias.

This study aims to examine whether pesticide retailers' recommendations aggravate pesticide overuse in China's rice production, accounting for potential self-selectivity bias arising from both observed and unobserved factors. Data from a random survey of 1084 farmers in four provinces in 2016 and the endogenous switching probit (ESP) model were used for the empirical analysis. The rest of this study proceeds as follows: Section 2 presents data and empirical methods. Section 3 reports the results and discussion, followed by robustness checks in Section 4. The concluding remarks are presented in the last section.

2. Theoretical Analysis and Methodology

2.1. Theoretical Analysis

Pesticide retailers' recommendations refers to farmers obtaining information regarding pesticide use from pesticide retailers. In China, pesticide retailers with dual roles not only sell pesticides, but also provide technical information to farmers [32]. Under the lack of governmental extension services, pesticide retailers have become one of the largest external information sources regarding pesticide use for farmers in China [22]. In this study, we consider that pesticide retailers' recommendations affect pesticide use in rice production in two ways. On the one hand, due to the fact that pesticide retailers are mainly composed of local farmers rather than professionals, they lack professional knowledge to provide correct technical information to farmers [33]. On the other hand, given that farmers are often faced with the high cost of obtaining technical information due to information asymmetry, pesticide retailers may provide misleading technical information to farmers to increase their commercial profit by using their advantages of possessing technical information [29]. Thus, pesticide retailers' recommendations might contribute to the increase in pesticide use for controlling pests.

2.2. Endogenous Switching Probit Model

It should be noted that there may be a potential self-selectivity bias arising from both observed and unobserved factors when econometrically estimating the impact of pesticide retailers' recommendations on farmers' pesticide overuse. Some observed and unobserved characteristics might simultaneously influence farmers' selection to obtain information from pesticide retailers and their pesticide overuse [8]. Ignoring this self-selectivity would result in biased estimated parameters [37]. To address this issue, this study employs the ESP model proposed by Lokshin and Sajaia [38], which consists of two-stage equations.

In the first stage, farmers' selection to obtain information from pesticide retailers for controlling a target pest is determined by multiple factors. Following a random utility maximization framework, this study assumes that farmers select to obtain information from pesticide retailers when the utility gained from obtaining information from pesticide retailers is greater than that gained from not obtaining information from pesticide retailers [39,40]. A farmer's probability of obtaining information from pesticide retailers for controlling a target pest is modeled as follows:

$$D_{ik}^* = \gamma Z_{ik} + \mu_{ik}, D_{ik} = \begin{cases} 1, & \text{if } D_{ik}^* > 0 \\ 0, & \text{if } D_{ik}^* \leq 0 \end{cases} \quad (1)$$

where D_{ik}^* is a latent variable that represents the probability of obtaining information from pesticide retailers for controlling the k -th target pest for the i -th farmer. Z_{ik} is a vector of exogenous variables influencing farmers' information acquisition from pesticide retailers, including farmers' individual, planting, and pest characteristics. γ is a vector of the parameters to be estimated, and μ_{ik} is an error term with a zero mean and normal distribution.

In the second stage, there are two dummy outcome equations representing pesticide overuse for farmers obtaining and not obtaining information from pesticide retailers:

$$O_{1ik}^* = \beta_1 X_{1ik} + \varepsilon_{1ik}, O_{1ik} = \begin{cases} 1, & \text{if } O_{1ik}^* > 0 \\ 0, & \text{if } O_{1ik}^* \leq 0 \end{cases} \text{ for } D_{ik} = 1 \quad (2)$$

$$O_{0ik}^* = \beta_0 X_{0ik} + \varepsilon_{0ik}, O_{0ik} = \begin{cases} 1, & \text{if } O_{0ik}^* > 0 \\ 0, & \text{if } O_{0ik}^* \leq 0 \end{cases} \text{ for } D_{ik} = 0 \quad (3)$$

where O_{1ik}^* and O_{0ik}^* are the latent variables describing the probability of pesticide overuse for controlling a target pest if a farmer obtains information from pesticide retailers or not, respectively. X_{1ik} and X_{0ik} are vectors of the exogenous variables. β_{1ik} and β_{0ik} are vectors of the parameters to be estimated. ε_{1ik} and ε_{0ik} are error terms. In the ESP model, the maximum likelihood estimation is used to simultaneously estimate Equations (1)–(3) [38].

The estimation of the ESP model needs at least one instrumental variable (IV) included in Z_{ik} but not in X_{1ik} and X_{0ik} [40,41]. The IV must be correlated with farmers' information acquisition from pesticide retailers but not correlated with their pesticide overuse except through obtaining information from pesticide retailers. Following Zhu et al. [42], this study adopted the proportion of farmers' neighbors obtaining information from pesticide retailers at the village level as the IV. This study used the falsification test to check the validity of this IV [43,44]. As shown in Table S1, the IV has a significantly positive effect on farmers' probability of obtaining information from pesticide retailers but had no significant effect on pesticide overuse among farmers not obtaining information from pesticide retailers. Therefore, the IV in this study is valid.

The advantage of the ESP model is that it can derive the treatment effects in both factual and counterfactual frameworks. After estimating the parameters in Equations (1)–(3), the treatment effects on the treated (TT) and untreated (TU) are derived as:

$$TT = \Pr(O_{1ik} = 1|D = 1) - \Pr(O_{0ik} = 1|D = 1) \\ = \frac{\Phi_2(\beta_1 X_{1ik}, \gamma Z_{ik}, \rho_1) - \Phi_2(\beta_0 X_{0ik}, \gamma Z_{ik}, \rho_0)}{F(\gamma Z_{ik})} \quad (4)$$

$$TU = \Pr(O_{1ik} = 1|D = 0) - \Pr(O_{0ik} = 1|D = 0) \\ = \frac{\Phi_2(\beta_1 X_{1ik}, -\gamma Z_{ik}, -\rho_1) - \Phi_2(\beta_0 X_{0ik}, -\gamma Z_{ik}, -\rho_0)}{F(-\gamma Z_{ik})} \quad (5)$$

where $F(\cdot)$ is the cumulative function of a univariate normal distribution, and Φ_2 is a cumulative function of a bivariate normal distribution [38]. ρ_0 and ρ_1 are the correlations between ε_{0ik} and μ_{ik} , and between ε_{1ik} and μ_{ik} , respectively. Equation (4) computes the treatment effect on the treated (TT), which is the difference in the probabilities of pesticide overuse for a pest-control observation in the factual (i.e., a farmer actually obtained information from pesticide retailers) and counterfactual contexts (i.e., a farmer obtaining information from pesticide retailers had not obtained information from pesticide retailers). Similarly, Equation (5) computes the treatment effect on the untreated (TU) [40,45].

This study further computes the treatment effects on the treated (ATT) and untreated (ATU) as:

$$ATT = \frac{1}{N_D} \sum_{i=1, k=1}^{N_D} \{ \Pr(O_{1ik} = 1|D = 1) - \Pr(O_{0ik} = 1|D = 1) \} \\ = \frac{1}{N_D} \sum_{i=1, k=1}^{N_D} \left\{ \frac{\Phi_2(\beta_1 X_{1ik}, \gamma Z_{ik}, \rho_1) - \Phi_2(\beta_0 X_{0ik}, \gamma Z_{ik}, \rho_0)}{F(\gamma Z_{ik})} \right\} \quad (6)$$

$$\begin{aligned}
 ATU &= \frac{1}{N_{N_{i=1, k=1}}} \sum_{i=1, k=1}^{N_N} \{ \Pr(O_{1ik} = 1 | D = 0) - \Pr(O_{0ik} = 1 | D = 0) \} \\
 &= \frac{1}{N_{N_{i=1, k=1}}} \sum_{i=1, k=1}^{N_N} \left\{ \frac{\Phi_2(\beta_1 X_{1ik}, -\gamma Z_{ik}, -\rho_1) - \Phi_2(\beta_0 X_{0ik}, -\gamma Z_{ik}, -\rho_0)}{F(-\gamma Z_{ik})} \right\} \quad (7)
 \end{aligned}$$

where N_D is the number of pest-control observations controlled by farmers obtaining information from pesticide retailers, and the N_N is the number of pest-control observations controlled by farmers not obtaining information from pesticide retailers.

2.3. Data

Data used in this study were collected through a farmer survey from October to November 2016. The survey covered four representative rice-producing provinces in the Yangtze River Basin in China, including Guizhou, Hubei, Jiangsu, and Zhejiang [24,25]. Note that the Yangtze River Basin (YRB) is the largest region of rice production in China, because nearly 70% of rice is produced in this area [46]. Moreover, Guizhou is located at the upper reach of the YRB; Hubei is located at the middle reach of the YRB; and both Jiangsu and Zhejiang are located in the lower reach of the YRB. Hence, these four provinces have good representativeness of a rice-producing region in China. Prior to the random sampling, all counties within each sampled province were divided into two groups based on per capita gross domestic product (GDP). Therefore, four counties from each sampled province were randomly selected, with two counties in each group. In a similar pattern, two townships in each sampled county and two villages in each sampled township were randomly selected. Within each selected village, about 20 rice farmers were randomly selected. Farmers that could not provide relevant information regarding pest management and pesticide use were excluded. The final sample included 1084 rice farmers.

In this survey, only the primary decision-maker regarding pesticide use in each sampled farmer was determined as the respondent. The objective of this study was to investigate whether pesticide retailers' recommendations aggravated pesticide overuse. To meet this objective, this study needs to identify whether each pest was controlled by overused pesticides, and thus, detailed information on farmers' pesticide applications was collected, including information on pesticide application in rice production, target pests controlled in each pesticide application, the corresponding names of all active ingredients applied for controlling each target pest, and the application rate of each active ingredient applied. In addition, the survey also collected information on the price of each active ingredient.

Moreover, the surveyed farmers were also asked to identify their major information sources with respect to the pesticide application rate in rice production in a multiple-choice question. In this study, the independent variable of interest is whether farmers acquire information from pesticide retailers. Hence, a dummy variable takes a value of one if a farmer acquires information on pesticide application from pesticide retailers, and zero otherwise. This study also considered three groups of exogenous variables that could affect farmers' information acquisition from pesticide retailers and pesticide overuse. The first group includes the farmer's individual characteristics, including gender, age, education level, status as a village leader, and participation in technology training. The second group included rice-planting characteristics, including sowing season, adoption of hybrid seed variety, and total rice sown area. The third group included pest characteristics referring to Sun et al. [15], including whether the target pest is a major pest, secondary pest, or weed.

2.4. Measuring Pesticide Overuse

This study defines pesticide overuse as the status when the actual pesticide application rate is higher than the scientifically recommended application rate provided by the Institute for the Control of Agrochemicals (<http://www.chinapesticide.org.cn/> (accessed on 5 November 2019)). Note that the Institute for the Control of Agrochemicals was established in 1963 as an institution affiliated with the Ministry of Agriculture and

Rural Affairs of China. The Institute specializes in nationwide pesticide registration and administration and is responsible for the registration, quality control, bioassay, and residue monitoring of pesticides, as well as the supervision of pesticide markets, information sharing, international cooperation, and other services. However, farmers often simultaneously apply different active ingredients of pesticides to control the same target pest in each application [24,25]. Since different active ingredients have heterogeneous ranges of scientifically recommended application rates, it is inappropriate to calculate a simple sum of the application rates of different active ingredients, and then define pesticide overuse by comparing the simply summed application rates of different active ingredients with the scientifically recommended application rates. To solve this problem, this study employed an index approach proposed by Zhang et al. [12] to convert actual application rates of different active ingredients for controlling each pest into an index application rate.

To measure pesticide overuse for each target pest, the concept of pest-control observation should be firstly defined. Given the fact farmers often apply different active ingredients to control several target pests in each pesticide application, the number of pest-control observations is equal to the number of target pests in each application [15]. Figure 1 shows the definition of pesticide overuse for each pest-control observation in each pesticide application.

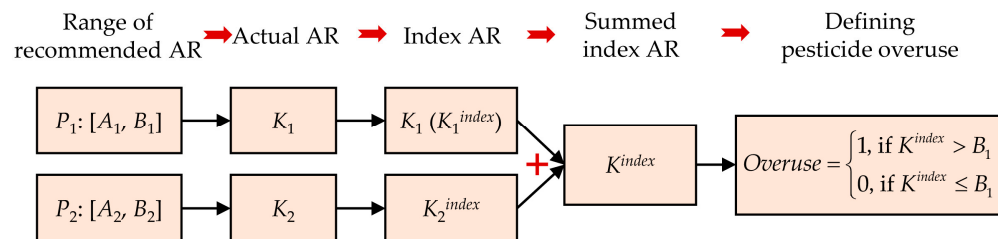


Figure 1. Schematic diagram for defining pesticide overuse for a pest-control observation. AR denotes the application rate.

As shown in Figure 1, without loss of generality, a pest-control observation is assumed as that in which a farmer applies two active ingredients (labeled as P_1 and P_2) to control a certain pest. In this pest-control observation, the actual application rates of P_1 and P_2 are K_1 and K_2 , respectively. The corresponding ranges of scientifically recommended application rates of P_1 and P_2 are $[A_1, B_1]$ and $[A_2, B_2]$, respectively. Of these two active ingredients, P_1 is selected as the referenced pesticide, and the index application rate of P_2 could be expressed as K_2^{index} in three scenarios:

$$K_2^{index} = \begin{cases} K_2 \times \left(\frac{A_1}{A_2}\right), & \text{if } K_2 < A_2 \\ \frac{[K_2 \times (B_1 - A_1) + (A_1 B_2 - A_2 B_1)]}{(B_2 - A_2)}, & \text{if } A_2 \leq K_2 \leq B_2 \\ K_2 \times \left(\frac{B_1}{B_2}\right), & \text{if } K_2 > B_2 \end{cases} \quad (8)$$

Note that the index application rate of the referenced pesticide (K_1^{index}) is equal to its actual application rate. Hence, the summed index application rates (K^{index}) of these two different active ingredients applied to control the same pest could be expressed as:

$$K^{index} = K_1^{index} + K_2^{index} \quad (9)$$

According to Zhang et al. [12], whether pesticides are overused or not to control the target pest can be defined as:

$$Overuse = \begin{cases} 1, & \text{if } K^{index} > B_1 \\ 0, & \text{if } K^{index} \leq B_1 \end{cases} \quad (10)$$

where the term *Overuse* denotes a dummy variable of pesticide overuse for a pest-control observation.

2.5. Descriptive Statistics

Table 1 presents the descriptive statistics of the main variables. It shows that approximately 29% of farmers obtained information from pesticide retailers. The average age of farmers was 57.13 years, and on average, farmers had 6.64 years of schooling. In addition, about 10 and 24% of farmers were village leaders and participated in technology training, respectively. The average total rice-sown area is only 2.01 ha, implying that the majority of farmers are small-scale rice producers. In addition, about 48 and 47% of farmers sowed rice in the late season and adopted hybrid varieties of rice, respectively, and the average price of active ingredients of pesticides was 133.93 CNY/kg.

Table 1. Descriptive statistics of main variables.

Variable	Definition	Mean (SD)
Pesticide retailers' recommendations	1 if a farmer obtains information from pesticide retailers, 0 otherwise	0.29 (0.45)
Male	1 if a farmer is male, 0 otherwise	0.90 (0.29)
Age	Age of farmer (years)	57.13 (9.62)
Education	Years of schooling of a farmer (years)	6.64 (3.27)
Village leader	1 if a farmer is a village leader, 0 otherwise	0.10 (0.30)
Technology training	1 if a farmer participates in technology training, 0 otherwise	0.24 (0.43)
Total rice sown area	Total sown size of rice (ha)	2.01 (11.14)
Late-season rice	1 if a farmer sows in late season, 0 otherwise	0.48 (0.50)
Hybrid rice	1 if a farmer adopts hybrid varieties, 0 otherwise	0.47 (0.50)
Pesticide price	Average price of active ingredients (CNY/kg)	133.93 (126.37)
Instrumental variable	Proportion of a farmer's neighbors obtaining information from pesticide retailers at the village level (%)	29.03 (14.45)
Number of farmers		1084

Notes: Data from the authors' survey. Figures in parentheses are standard deviations. Please see descriptive statistics of main variables across provinces in Table S2.

The mean differences in those main variables between farmers obtaining and not obtaining information from pesticide retailers are presented in Table 2. Compared with those not obtaining information from pesticide retailers, farmers obtaining information from pesticide retailers were more likely to be male, older and less educated, and less likely to be a village leader, have lower participation in technology training, and have a higher proportion of neighbors obtaining information from pesticide retailers at the village level. Note that these significant differences might imply the presence of self-selectivity bias.

Figure 2 presents the distribution of pest-control observations in this study. In total, there were 7171 pest-control observations in the survey, but the proportion of pest-control observations greatly differed across pest category. Specifically, pest-control observations for controlling major pests, secondary pests, and weeds accounted for 69.10, 10.14, and 20.76%, respectively. There were 1926 pest-control observations for farmers obtaining information from pesticide retailers, including 67.55, 10.23, and 22.22% of pest-control observations controlling major pests, secondary pests, and weeds, respectively. In contrast, there were 5245 pest-control observations for those farmers not obtaining information from pesticide retailers, including 69.67, 10.10, and 20.23% of pest-control observations for controlling major pests, secondary pests, and weeds, respectively.

Table 3 shows the proportion of pesticide-overuse observations for different categories of pests. In terms of all observations, the average proportion of pesticide-overuse observations was 54.43%. On average, the proportion of pesticide-overuse observations for controlling major pests, secondary pests, and weeds was 58.49, 55.02, and 40.63%, respectively. It also provides that relative to those not obtaining information from pesticide retailers, the proportion of pesticide-overuse observations among farmers obtaining information from pesticide retailers for controlling all pests and major pests was higher by 2.82 and 5.01%, respectively. However, there was no significant mean differences of the

proportion of pesticide-overuse observations for controlling secondary pests and weeds between those two groups of farmers.

Table 2. Mean differences between farmers obtaining and not obtaining information from pesticide retailers.

Variable	Farmers Obtaining Information from Pesticide Retailers	Farmers not Obtaining Information from Pesticide Retailers	Mean Differences
Male (1 = yes, 0 = no)	0.91 (0.28)	0.90 (0.30)	0.01
Age (years)	58.11 (9.75)	56.72 (9.55)	1.38 **
Education (years)	5.99 (3.36)	6.91 (3.20)	−0.92 ***
Village leader (1 = yes, 0 = no)	0.06 (0.24)	0.11 (0.32)	−0.05 **
Technology training (1 = yes, 0 = no)	0.14 (0.35)	0.29 (0.45)	−0.15 ***
Total rice sown area (ha)	1.04 (3.46)	2.40 (13.03)	−1.36 *
Late-season rice (1 = yes, 0 = no)	0.47 (0.50)	0.48 (0.50)	0.01
Hybrid rice (1 = yes, 0 = no)	0.49 (0.50)	0.47 (0.50)	0.03
Pesticide price (RMB/kg)	136.53 (130.98)	132.86 (124.5)	3.67
Instrumental variable (%)	32.59 (15.11)	27.57 (13.91)	5.02 ***
Number of farmers	316	768	

Notes: Data from the authors' survey. Figures in parentheses are standard deviations. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

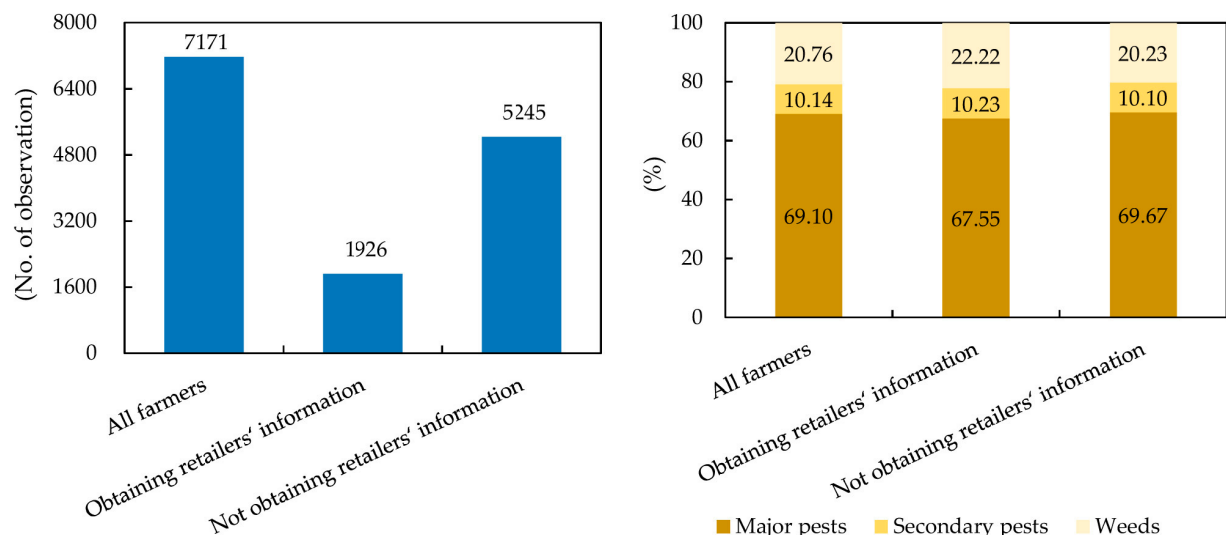


Figure 2. Number and distribution of pest-control observations. Please see more details in Table S3.

Table 3. Proportion of pesticide-overuse observations (%).

Pest Category	All Farmers	Farmers Obtaining Information from Pesticide Retailers	Farmers Not Obtaining Information from Pesticide Retailers	Mean Differences
All pests	54.43	56.49 (0.50)	53.67 (0.50)	2.82 **
Major pests	58.49	62.18 (0.49)	57.17 (0.49)	5.01 ***
Secondary pests	55.02	59.39 (0.49)	53.40 (0.50)	5.99
Weeds	40.63	37.85 (0.49)	41.75 (0.49)	−3.90

Notes: Figures in parentheses are standard deviations. *** and ** indicate the significance at the 1% and 5% level, respectively. Please see more details in Table S4.

3. Results and Discussion

The estimation results of the ESP model are presented in Table 4. In the lower panel of Table 4, ρ_0 and ρ_1 are significant and negative for both farmers obtaining and not obtaining information from pesticide retailers. These results indicate that farmers' decision

to obtain information from pesticide retailers was not random, implying the presence of a self-selectivity bias [45,47]. The χ^2 statistics for the Wald test of independent equations were significant, further indicating that the selection and outcome equations were dependent [38,48]. Hence, it is necessary and appropriate to employ the ESP model to account for the self-selectivity bias in this study.

Table 4. Estimated results of the endogenous switching probit model.

Variable	Selection Equation	Outcome Equation (Pesticide Overuse)	
		Farmers Obtaining Information from Pesticide Retailers	Farmers Not Obtaining Information from Pesticide Retailers
Male	0.227 *** (0.060)	0.250 ** (0.127)	0.028 (0.054)
Age	0.001 (0.002)	0.000 (0.003)	0.002 (0.002)
Education	−0.033 *** (0.006)	−0.017 (0.013)	0.016 *** (0.005)
Village leader	−0.384 *** (0.062)	0.268 ** (0.126)	0.109 ** (0.051)
Technology training	−0.393 *** (0.043)	0.235 ** (0.100)	0.026 (0.037)
Total rice sown area	−0.013 *** (0.003)	−0.001 (0.007)	0.004 *** (0.001)
Late-season rice	−0.237 *** (0.039)	0.031 (0.078)	0.268 *** (0.038)
Hybrid rice	0.220 *** (0.037)	−0.021 (0.078)	−0.064 ** (0.035)
Pesticide price	0.000 ** (0.000)	0.000 (0.000)	−0.001 *** (0.000)
Major pests	−0.004 (0.054)	0.101 (0.089)	0.104 ** (0.051)
Weeds	0.053 (0.062)	−0.421 *** (0.111)	−0.244 *** (0.059)
Instrumental variable	0.006 *** (0.001)		
Constant	−1.095 *** (0.159)	0.643 (0.429)	−0.276 * (0.147)
District dummy	Controlled	Controlled	Controlled
ρ_1		−0.586 *** (0.207)	
ρ_0			−0.976 *** (0.026)
Wald test of indep. eqns. ($\rho_1 = \rho_0$)		chi ² (2) = 19.84	Prob > chi2 = 0.0000
Observations		7171	

Notes: Figures in parentheses are standard errors. ***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively. The reference pest category is the secondary pests.

3.1. Determinants of Obtaining Information from Pesticide Retailers

The results on determinants of farmers' information acquisition from pesticide retailers are presented in the first column in Table 4. First, several individual characteristics have significant impacts on farmers' information acquisition from pesticide retailers. For example, it shows that gender (male) is an important determinant. In comparison to female farmers, male farmers were more likely to obtain information from pesticide retailers. Most women in rural areas have lower educational attainments and less access to training [49,50]. Consequently, they tend to make decisions regarding pesticide use based on their own experience. The results also showed a significantly negative coefficient of education and technology training, indicating that better education and participation in technology train-

ing reduced the probability of obtaining information from pesticide retailers. Indeed, education and technology training are important in determining a farmer's pesticide use knowledge. When making decisions regarding pesticide use, farmers with a higher level of knowledge typically do not rely on pesticide retailers' recommendations, as pesticide retailers could have a lower level of knowledge than them [30,51]. Similarly, the coefficient of village leader is significantly negative, indicating that village leaders were less likely to obtain information from pesticide retailers.

Second, farmers' planting and pest characteristics can also affect their information acquisition from pesticide retailers (Table 4). The coefficient of total rice sown area was significant and negative, indicating that the rice sown area impacts the selection to obtain information from pesticide retailers. In line with Caffaro et al. [52], the results show that large-scale farmers had more opportunities to access different information sources; they may have more opportunities to access professional technology information from government representatives and research institutions. Furthermore, the coefficient of late-season rice was negative, but the coefficient of hybrid rice was positive, indicating that farmers planting late-season rice were less likely to obtain information from pesticide retailers, whereas farmers planting hybrid rice were more likely to do so. Pesticide price also had a significantly positive impact on the selection to obtain information from pesticide retailers, albeit with a small coefficient. As expected, the IV was positive and significant. It is worth emphasizing here that the objective of setting the selection to obtain information from pesticide retailers at the first stage of the ESP model was to control for unobserved heterogeneities that may bias the effect of pesticide retailers' recommendations on pesticide overuse [40].

3.2. Effect of Pesticide Retailers' Recommendations on Pesticide Overuse

The effects of pesticide retailers' recommendations on pesticide overuse are calculated and presented in Table 5. The ATT of 0.565 suggested that obtaining information from pesticide retailers increased the probability of pesticide overuse for controlling each observation by 56.5%. The positive and significant ATU implied that for farmers' not obtaining information from pesticide retailers, the probability of pesticide overuse for controlling each observation would increase by 33.6% if they had obtained information from pesticide retailers. These findings in this study are consistent with Jin and Bluemling [23] and Li et al. [33], who reported that pesticide retailers might recommend higher application rates than scientifically recommended levels to increase their commercial profits.

Table 5. Average treatment effects of pesticide retailers' recommendations on pesticide overuse.

Pest Category	ATT	ATU
All pests	0.565 *** (0.133)	0.336 *** (0.091)
Major pests	0.621 *** (0.090)	0.330 *** (0.092)
Secondary pests	0.593 *** (0.079)	0.361 *** (0.081)
Weeds	0.383 *** (0.097)	0.348 *** (0.088)

Notes: Figures in parentheses are standard deviations. *** indicates the significance at the 1% level.

Moreover, given the significant impact of the pest category on pesticide overuse, this study examined the impacts of pesticide retailers' recommendations on pesticide overuse across different pest categories. The results are also presented in Table 5. Obtaining information from pesticide retailers to control major pests, compared with secondary pests and weeds, had a larger positive effect on pesticide overuse. The ATT estimates showed that obtaining information from pesticide retailers increased the probability of pesticide overuse for controlling major pests by 62.1%; the effect for controlling secondary pests and weeds was to increase the probability of pesticide overuse by 59.3 and 58.3%, respectively. Similarly, for farmers not obtaining information from pesticide retailers, the probability of pesticide overuse for controlling major pests, secondary pests, and weeds would increase by 33.0, 36.1, and 34.8%, respectively, if they had obtained information from pesticide retailers.

3.3. Other Factors Influencing Pesticide Overuse

Table 4 also reports that other factors may also significantly influence pesticide overuse. For example, farmers' gender might have different impacts on pesticide overuse for farmers obtaining and not obtaining information from pesticide retailers. Male farmers were more likely to overuse pesticides for controlling pests. Meanwhile, there was no significant gender differences in pesticide overuse for farmers not obtaining information from pesticide retailers. Similarly, education, technology training, total rice sown area, late-season rice, and hybrid rice also showed different impacts on pesticide overuse for two groups of farmers.

Table 4 shows that there is a positive and statistically significant coefficient of the dummy variable of village leader, implying that village leaders were more likely to overuse pesticides. This finding differs from that provided by Feng et al. [53]. One possible explanation is that Chinese village leaders are mainly busy with administrative work, and thus, might apply excessive pesticides to reduce labor input in agricultural production.

The category of controlled pests was related to farmers' pesticide use [15]. In both outcome equations, the coefficients of weed were negative and statistically significant, implying that compared with secondary pests, the probability of pesticide overuse for controlling weeds would be smaller. This finding is in line with Sun et al. [22], who reported that the average proportion of pesticide-overuse observations for controlling weeds is smaller than that for controlling secondary pests.

4. Robustness Check

To check the robustness of results mentioned above, this study employed the conditional mixed process (CMP) model proposed by Roodman [54] to estimate the average treatment effect of pesticide retailers' recommendations on pesticide overuse. The CMP model can also address the potential self-selectivity bias caused by both observed and unobserved factors, thereby allowing us to estimate equation systems for dependent variables of a different nature [55]. More specifically, this study jointly estimated a probit model that explains the dummy variable of whether a farmer would obtain information from pesticide retailers (selection equation) and a probit model for the dummy variable of pesticide overuse (outcome equation).

According to the estimation results of the CMP model, the coefficient of atanhrho_{12} denotes the correlation between error terms of selection and outcome equations, which was significant and negative (Table 6). This indicates the presence of self-selectivity bias. As expected, this study found that pesticide retailers' recommendations exerted an overall positive effect on pesticide overuse. The coefficient of pesticide retailers' recommendations was positive and significant, indicating that obtaining information from pesticide retailers increased the probability of pesticide overuse. This result is consistent with the average treatment effects of pesticide retailers' recommendations on pesticide overuse in Table 5. In addition, several other exogenous variables were also significantly correlated with pesticide overuse. For instance, the variables of gender, age, status of village leader, total rice sown area, and late-rice plantation showed significant and positive effects on pesticide overuse. However, the coefficient of pesticide price was significant and negative, indicating that appropriate price regulation can mitigate pesticide overuse [2].

This study also analyzed the impact of pesticide retailers' recommendations on pesticide index application rate using the CMP model. For this purpose, this study jointly estimated a probit model that explains the dummy variable of selection to obtain information from pesticide retailers (selection equation) and a linear regression model for the index application rate of pesticides (outcome equation). The CMP results, shown in Table 7, revealed that obtaining information from pesticide retailers was significantly and positively associated with the index application rate of pesticides, thereby confirming that pesticide retailers' recommendations can increase the index application rate of pesticides.

Table 6. Estimated results of the conditional mixed process model.

Variable	Selection Equation	Outcome Equation (Pesticide Overuse)
Pesticide retailers' recommendations		1.115 *** (0.161)
Male	0.239 *** (0.060)	0.111 ** (0.056)
Age	0.002 (0.002)	0.004 ** (0.002)
Education	−0.032 *** (0.006)	0.005 (0.006)
Village leader	−0.366 *** (0.062)	0.103 ** (0.051)
Technology training	−0.375 *** (0.043)	0.010 (0.045)
Total rice sown area	−0.013 *** (0.003)	0.003 ** (0.001)
Late-season rice	−0.230 *** (0.040)	0.199 *** (0.037)
Hybrid rice	0.208 *** (0.037)	−0.004 (0.040)
Pesticide price	0.000 *** (0.000)	−0.001 *** (0.000)
Major pests	−0.022 (0.055)	0.098 ** (0.048)
Weeds	0.038 (0.063)	−0.320 *** (0.057)
Instrumental variable	0.007 *** (0.001)	
Constant	−1.163 *** (0.161)	−0.382 *** (0.139)
District dummy atanrho_12	Controlled	Controlled −0.807 *** (0.191)
Observations		7171

Notes: Figures in parentheses are standard errors. *** and ** indicate the significance at the 1% and 5% level, respectively. The reference pest category is the secondary pests.

Table 7. Estimated effects of pesticide retailers' recommendations on index application rate of pesticides.

Variable	Selection Equation	Outcome Equation (Log of Index Application Rate)
Pesticide retailer recommendation		0.829 *** (0.230)
Male	0.295 *** (0.089)	−0.258 *** (0.083)
Age	0.003 (0.003)	0.001 (0.003)
Education	−0.044 *** (0.008)	−0.001 (0.008)
Village leader	−0.267 *** (0.085)	0.106 (0.074)
Technology training	−0.291 *** (0.060)	−0.119 ** (0.057)
Total rice sown area	−0.018 *** (0.005)	0.002 (0.002)
Late-season rice	−0.328 *** (0.054)	−0.057 (0.059)

Table 7. Cont.

Variable	Selection Equation	Outcome Equation (Log of Index Application Rate)
Hybrid rice	0.166 *** (0.051)	−0.008 (0.051)
Pesticide price	0.001 *** (0.000)	−0.003 *** (0.000)
Major pests	−0.055 (0.075)	−0.051 (0.071)
Weeds	0.002 (0.092)	0.139 (0.087)
Instrumental variable	0.008 *** (0.002)	
Constant	−1.304 *** (0.236)	7.303 *** (0.216)
District dummy atanrho_12	Controlled	Controlled −0.368 *** (0.109)
Observations		7171

Notes: Figures in parentheses are standard errors. *** and ** indicate the significance at the 1% and 5% level, respectively. The reference pest category is the secondary pests.

5. Conclusions and Policy Implications

This study investigated the determinants of farmers' selection to obtain information from pesticide retailers, and the impact of pesticide retailers' recommendations on pesticide overuse. Cross-sectional survey data collected from a randomly selected sample of 1084 rice farmers in Guizhou, Hubei, Jiangsu, and Zhejiang in 2016 were used. This study employed the ESP model to address potential self-selectivity bias arising from both observed and unobserved factors. The CMP model was further utilized for the robustness check. The results showed that the average proportion of pesticide-overuse observations was 54.43%. Relative to those not obtaining information from pesticide retailers, the proportion of pesticide-overuse observations for farmers obtaining information from pesticide retailers was higher by 2.82%. After addressing the self-selectivity bias, this study confirmed that pesticide retailers' recommendations increased the probability of pesticide overuse by 56.5%, and consistent results were found for controlling major pests, secondary pests, and weeds, separately.

This study has some important policy implications. First, governmental departments should provide pesticide retailers with additional technical training regarding pesticide use, such as pesticide application rate and timing. Numerous studies have shown that pesticide retailers possess poor knowledge of pest control and crop protection, resulting in incorrect recommendations regarding active ingredients and application rates [23]. Additional technology training, therefore, should be provided by governmental extension agents to improve the knowledge of pesticide retailers. Second, more efforts should be made to regulate pesticide retailers' behavior regarding sales and information recommendations. Due to moral hazard and information asymmetry, pesticide retailers have often been accused of providing misleading information to farmers to increase their commercial profits. However, highly intensive governmental regulations may be able to reduce the probability of provision of misleading information among pesticide retailers, which would be helpful in mitigating pesticide overuse in crop production. Hence, government departments should enhance the enforcement of regulations on the supervision and management of pesticide retailers. Third, improving socialized agricultural technology service systems, such as outsourcing pest management, is a crucial measure to avoid pesticide overuse. Outsourcing pest management refers to farmers delegating pest-control tasks to other individuals or organizations that specialize in providing pest management services [56]. Given the presence of information asymmetry between farmers and information providers,

the outsourcing of pest management can serve as a beneficial solution for farmers with limited access to technology information. By doing so, it can help farmers overcome knowledge constraints and effectively prevent pesticide overuse [57]. Thus, additional support policies should be implemented to promote the outsourcing of pest management in rural China.

This study also provides valuable insights for addressing pesticide overuse in other developing countries. With the absence of professional agricultural extension services, pesticide retailers have become primary information sources, leading to farmers overusing pesticides in developing countries, such as Iran, Vietnam, and Nepal [10,49,58]. Thus, policymakers can implement several strategies to effectively provide pesticide retailers with additional technology training and develop enhanced services for outsourcing pest management. It is expected that this will decrease the probability of pesticide overuse.

In addition, this study also has several limitations. First, the analysis in this study only focuses on rice farmers, which might limit its generalizability to the production of other agricultural products. Second, this study mainly relies on farmers' self-reported data, and thus, may be subject to potential reporting bias and measurement error. Meanwhile, data used in this study are relatively old, which might not be enough to reflect the latest evolution of the relationship between pesticide retailers' recommendations and farmers' pesticide overuse. Third, while the index approach can facilitate the aggregation of active ingredients of pesticides with different ranges of scientifically recommended application rates, it fails to clarify whether the application of an active ingredient would affect the effectiveness of other active ingredients when there is a mixed application of different active ingredients.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture13071301/s1>, Table S1: Estimation results of falsification test of instrumental variable; Table S2: Descriptive statistics of main variables across provinces; Table S3: Number of pest-control observations and average index application rate for each pest; Table S4: Number and proportion of pesticide-overuse observations.

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