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Can mechanized pesticide application help reduce pesticide use and increase crop yield? Evidence from rice farmers in Jiangsu province, China

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ABSTRACT

This study is devoted to analyzing the effects of outsourcing machinery-intensive farming activities vis-à-vis using mechanized equipment in-house on pesticide use, utilizing cross-sectional data collected from rice farmers in Jiangsu province, China. The control function approach is utilized to address the endogeneity of the decision to outsource pesticide application or complete the task in-house. Our results suggest that outsourcing pesticide application decreases pesticide expenditure but in-house application using mechanized equipment increases it. Specifically, outsourcing pesticide application reduces pesticide expenditure by about 81 yuan per mu or around 0.18 yuan per kilogram of rice produced. In comparison, the in-house application using mechanized equipment increases pesticide expenditure by 118 yuan per mu or by 0.14 yuan per kilogram of rice output. We also find that both outsourcing and in-house pesticide applications increase rice yield.

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1. Introduction

Pesticides have been a boon for agricultural production and food security. However, they have also been linked to environmental degradation, adverse effects on human health, and loss of biodiversity (Andersson & Isgren, 2021; Li et al., 2022; Meftaul et al., 2023). Overuse of chemical pesticides increases production costs, depletes natural resources integral to producing them, and contaminates soil, water, turf, and other vegetation (Choudhary et al., 2018). Certain types of pesticides can be quite injurious to humans. For example, non-glyphosate herbicides can induce renal dysfunction and decrease serum folic acid, and chemical lepidopteran insecticides may cause inflammation, serum glucose elevation, hepatic dysfunction, and even severe nerve damage (Zhang et al., 2016). The manifold adverse effects of pesticide overuse have prompted governments worldwide to implement various programs and policies to reduce pesticide use and promote sustainable agriculture.

Historically, smallholders in developing countries have applied pesticides using manual sprayers (Wang et al., 2020a; Zheng et al., 2019). Recently, however, advances in technology and the emergence of agricultural service providers have led to the uptake of mechanized equipment such as motor-driven mist machines and electrostatic sprayers for spraying pesticides (Danso-Abbeam & Baiyegunhi, 2018; Wang et al., 2020a; Zheng et al., 2019). For example, 6.15 million motorized machines were used for spraying pesticides in China in 2019 (CMIIRI, 2019). Nevertheless, many households cannot access, afford, or use advanced machines such as unmanned aerial vehicles (UAVs) and industrial-grade pesticide-application equipment.

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Such farmers generally outsource pesticide application and, thus, utilize technology such as UAVs that would otherwise be unavailable to them (Zheng et al., 2019). In sum, farmers can buy the requisite equipment to spray pesticides on their own, outsource pesticide application, or do both. Although mechanized equipment can be rented as well, this is not common in China because farmers seldom have the technical know-how to operate such equipment.[1] Generally, using machines instead of manual sprayers has several advantages: it improves the precision of pesticide delivery, increases farm efficiency, saves time, and boosts productivity (Sun et al., 2018). Be that as it may, because applying pesticides using machines is relatively convenient and costless, farmers may spray more often and thus overuse pesticides (Li et al., 2023b).

Most studies on agricultural machinery have focused on their impact on farm performance. There are three main strands of this literature. The first strand examines the impact of machine use on farm production without accounting for the source of the machines (i.e. outsourced or household-owned) (e.g. Ma et al., 2022; Mano et al., 2020; Paudel et al., 2019). For example, Zhou et al. (2020) found that using farm machinery significantly increases maize yield in China and reduces the inequality and variability of maize yield. Mano et al. (2020) showed that using tractors to prepare the land significantly increases rice yield because it induces farmers to implement proper agronomic practices. The second strand mainly looks at the effects of outsourcing machinery-intensive tasks on farm production (e.g. Baiyegunhi et al., 2019; Deng et al., 2020; Qu et al., 2021). Analyzing data on China, Deng et al. (2020) concluded that outsourcing machinery services can increase agricultural productivity by 25.61%. Qu et al. (2021) showed that outsourcing harvesting significantly reduces field harvest losses of rice in China. Comprising only a few studies (Qian et al., 2022; Zheng et al., 2019), the third strand examines both outsourcing machinery-intensive tasks and using household-owned farm machinery and reports interdependence between the two. Qian et al. (2022) noted a complementary relationship between outsourcing and in-house completion of farming activities. Combining the two increases the probability of renting-in land but decreases the probability of renting-out land among Chinese households.

Only a few studies have investigated the association between farm machinery use and pesticide application. Recent examples include Zhang et al. (2019) and Li et al. (2023b), who analyzed data on China, and Kaiser and Burger (2022), who examined Swiss data. Zhang et al. (2019) found that using farm machinery decreased the pesticide expenditure of maize farmers. One may surmise from these results that pesticide expenditure declined due to an increase in the use of agricultural machinery. Li et al. (2023b) estimated province-level panel data on China and found that specialized agricultural services, typically machinery service, can directly increase the intensity of pesticide use. Overall, there is a lack of consensus regarding the association between agricultural machinery use and pesticide application. Meanwhile, the literature analyzing the heterogenous impacts of agricultural machinery use on pesticide application regarding the source of the machines (i.e. outsourced or household-owned) remains thin.

We make three contributions to the literature by examining how and to what extent mechanized pesticide application affects pesticide use. First, we investigate the association between agricultural machinery use and pesticide application by comparing the effects of outsourcing pesticide application and spraying pesticides in-house on pesticide expenditure. Then, we analyze the impact of agricultural machinery use on pesticide reduction; at this stage, we examine whether relying on outsourced machinery service, household-owned machinery, or both lower pesticide use. It bears emphasis that in-house pesticide application can be accomplished using manual sprayers or mechanized equipment – in this study, we focus on the role of the latter. To distinguish it from outsourced services, we define it as farmers themselves spraying pesticides using their own machinery. Outsourcing, on the other hand, entails the use of mechanized equipment, as these services are offered by commercial operations with ready access to mechanized equipment. Thus, in the context of the present study, outsourcing pesticide application is accomplished using machinery rather than manual sprayers. Consistent with previous studies (Jaraite & Kažukauskas, 2012; Ma & Zheng, 2022), we measure pesticide consumption monetarily rather than quantitatively because farmers apply different types of pesticides (e.g. granular, powdered, coated, and fluid pesticides). Having a common denominator, i.e. pesticide expenditure, helps us compare and analyze pesticide use. Second, we employ a control function approach to address the potential endogeneity of outsourcing pesticide application and using mechanized equipment to complete the same task in-house. To be clear, farmers *choose* whether to outsource (Deng et al., 2020; Ji et al., 2017; Qu et al., 2021) or complete the task on their own (Ma, Renwick, et al., 2018; Zheng et al., 2021; Zhou et al., 2020). These decisions are influenced by both observed factors (e.g. age, sex, education, and household income) and unobserved factors (e.g. motivations), making them endogenous – the endogeneity may lead to biased estimates. Third, as noted above, we also examine how outsourcing pesticide application and spraying pesticides using mechanized equipment in-house affect pesticide expenditure per unit of crop output and rice yield. This can improve our understanding of the association between agricultural machinery use and pesticide application.

China is the largest pesticide consumer in the world (Figure 1). In 2019, China consumed 1.77 million tons of pesticides, which is significantly higher than the United States, Brazil, and Argentina, three of the largest pesticide consumers globally (Global agriculture towards, 2050, 2009). The Chinese government has made great efforts to reduce the application of agrochemicals such as pesticides. In February 2015, the Ministry of Agriculture and Rural Affairs of the People's Republic of China (MARAC) introduced two action plans to regulate pesticide use and eliminate the excessive application of pesticides. These include the 'Action plan for zero growth in pesticide use by 2020' and the 'Action plan for tackling the agricultural and rural pollution control.' (Jin & Zhou, 2018; Zhao et al., 2021). The Chinese government has also initiated a 'Green Pest Control' subsidy program to help reduce pesticide application (Wei et al., 2019). These efforts have proven effective. China's pesticide consumption has shown a dramatic decreasing trend since 2015. Official data from MARAC shows that pesticide use in mainland China decreased by about 5% annually from 2015 to 2019 (NSBC, 2021). However, there is room for improvement. In 2019, China's pesticide consumption per hectare was 8.39 kg, more than twice that of the second-largest pesticide-consuming country, the United States.

We use data on Jiangsu province, China, collected by Nanjing Agricultural University through the China Land Economic Survey (CLES) project. Jiangsu province is one of the highest consumers of pesticides in China. In 2020, it consumed 65 thousand tons of pesticides, ranking 8th in China. The inappropriate and excessive application of pesticides in Jiangsu is concerning. For example, a recent study by Ma et al. (2020) reports that the average DDT concentration in soil in Jiangsu province is near 100 , which significantly exceeds the national standard, 50 $\mu g/kg$. According to the data released by the Jiangsu Provincial Center for Disease Control and Prevention, 40,690 pesticide poisoning cases occurred in Jiangsu province from 2006 to 2020. This underscores the need for effective strategies to control pesticide use in areas like Jiangsu province. Additionally, Jiangsu province encapsulates many of the characteristics of China – northern, central, and southern Jiangsu reflect agricultural mechanization, agricultural production, and economic conditions in western, central, and eastern China (Li et al., 2023a). Therefore, findings stemming from Jiangsu have important

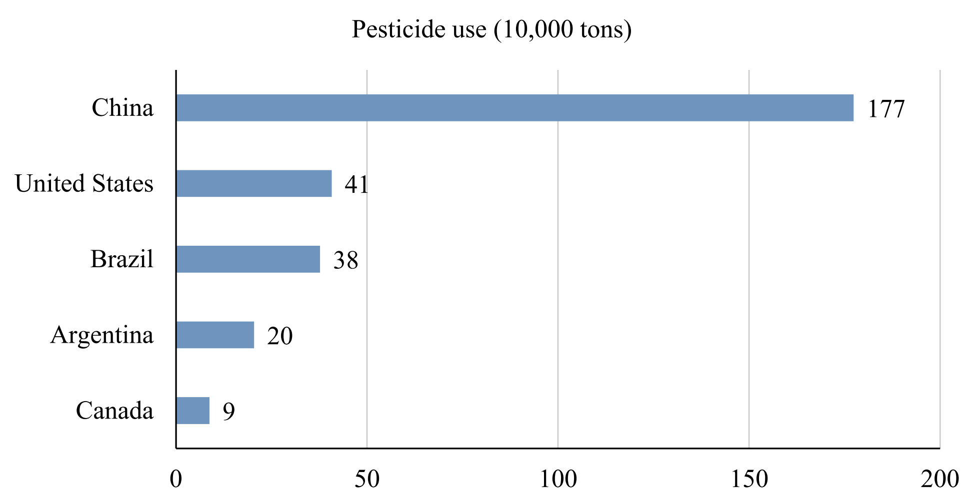

Figure 1. Top five pesticide use countries in 2019. Source: FAO data.

implications for China as a whole, making the province a useful case study.

The rest of this paper is structured as follows. Section 2 provides a brief background on agricultural mechanization and outsourcing farming activities in China. Section 3 explains the estimation strategy. Section 4 presents the data and descriptive statistics. Section 5 discusses the empirical results. The final section concludes the paper, lays out policy implications, and declares research limitations.

2. Background

2.1 Agricultural mechanization in China

Mechanizing agriculture is integral to modernizing it. In the twenty-first century, China has made great efforts to this end. Since 2004, with the enactment of the '*Law of the People's Republic of China on the Promotion of Agricultural Mechanization*,' over 300 billion yuan have been paid to farmers by the government in the form of agricultural machinery purchase subsidies. There is a marked improvement in agricultural mechanization across the country. According to data released by MARAC, the total power of agricultural machinery (TPAM) reached 1,056.22 gigawatts at the end of 2020, an increase of 64.96% compared to 2004 (NSBC, 2021). Meanwhile, the proportions of the machine-ploughed area, machine-sewn area, and mechanical harvesting area in 2019 reached 74.81%, 57.30%, and 61.40%, respectively (CMIIRI, 2019). However, China's agricultural mechanization is far from complete. For example, official data show that the proportion of mechanical crop protection (e.g. pesticide spraying) area only reached 44.89% in 2019 (CMIIRI, 2019), highlighting the need to accelerate agricultural mechanization.

2.2 Outsourcing machinery-intensive farming activities in China

To accelerate agricultural mechanization, China has promoted outsourcing farm activities in recent decades (Yang et al., 2013). At present, China has developed an elaborate system designed to help farmers outsource machinery-intensive tasks. It comprises government agricultural machinery service agencies, combined service enterprises, family farms, and individual farmers who own agricultural machines. The number of such service organizations in China increased from 170.6 thousand in 2011–192.2 thousand in 2019 (CMIIRI, 2019). Correspondingly, people engaged in agricultural machinery services increased from 1,195 thousand to 2,133 thousand in the same period (CMIIRI, 2020).

Indeed, outsourcing machinery-intensive farming activities has significantly improved China's agricultural mechanization (Nanjing Institute of Agricultural Mechanization, 2019) and has generated substantial economic benefits. The national income from using agricultural machinery reached a staggering 512.5 billion dollars in 2019 (CMIIRI, 2019). This is all the more impressive considering the dearth of organizations to which machinery-intensive farming activities can be outsourced: there is one for every 1,000 hectares of arable land in China (CMIIRI, 2019). Unsurprisingly, fewer than 50% of Chinese farmers have outsourced farming activities.

2.3 Agricultural mechanization in Jiangsu province, China

Jiangsu, one of China's leading rice-producing provinces, cultivated 2,202.84 thousand hectares and provided 19.66 million tons of rice in 2020; it ranked 6th and 4th in area cultivated and production, respectively, among the 31 provinces of China (NSBC, 2021). However, agricultural mechanization in the province has not kept pace with its output. For example, the TPAM per hectare in Jiangsu province was only 7.0 kilowatts in 2020, ranking 13th in China (NSBC, 2021). The proportion of machine-sewn area rice farms in Jiangsu province was only 12.0% in 2019 (CMIIRI, 2019); there were only 1.7 organizations per 1,000 hectares in the province catering to farmers' demand for mechanized farming services (CMIIRI, 2019). Jiangsu province offers a nationally representative case of China's agricultural mechanization. Analyzing pesticide use in Jiangsu would provide meaningful insights that may be applied to reduce pesticide use and promote agricultural mechanization throughout China.

3. Conceptual framework and estimation strategy

3.1 Conceptual framework

Outsourcing machinery service and in-house machinery use are inherently different. Professional agricultural services providers use more advanced tools and techniques – they are more adept at completing outsourced tasks than the farmers to whom they offer these services. For example, professional service providers use industrial-grade sprayers and UAVs for spraying pesticides. On the other hand, most smallholders use inexpensive and basic spraying machines (Davis & Lopez-Carr, 2014; Yang et al., 2013). Thus, professional service providers complete the tasks more proficiently.

Furthermore, due to their expertise and access to better equipment, professional service providers are more likely than farmers to apply the appropriate pesticides in the proper concentrations. Therefore, outsourcing pesticide application can increase input use efficiency. By leveraging economies of scale, professional service providers can bargain for low-cost, high-quality agricultural inputs (Wolf, 2003). As a result, outsourcing machinery services can provide farmers with better pesticides, helping them reduce the intensity of pesticide use.

The evidence that in-house machinery use increases farmers' pesticide application is suggestive. In the next section, we discuss the empirical models used for investigating the impacts of outsourcing machinery service and in-house machinery use on pesticide application in Jiangsu, China.

3.2 Estimation strategy

3.2.1 Estimation issues

To apply pesticides using machines, farmers are faced with two choices: whether to outsource pesticide application or use mechanized equipment in-house to spray pesticides. Should farmers outsource pesticide application, not only will they save time and obviate the need to purchase inputs and equipment needed to spray pesticides, but they may also optimize the amount of pesticide sprayed, leading to better environmental outcomes. Specialists offering these services apply the amount necessary to achieve the desired results, thus preventing overspraying. Alternatively, farmers may complete this task using mechanized equipment in-house because outsourcing may be costly. Also, outsourcing machinery services may not be available in some places due to underdeveloped markets.

Farmers' decisions to use outsource machinery services and complete tasks using the in-house machinery are influenced by observed household and individual-level characteristics (e.g. age, education, household size, and farm size) and socioeconomic conditions (e.g. availability of service providers) (Aryal et al., 2021; Daum et al., 2022; Ma, Renwick, et al., 2018b). Unobserved factors (e.g. farmers' motivations and innate abilities) may also affect farmers' decisions to outsource pesticide application. For example, farmers who want to participate in non-farm work may be more likely to outsource pesticide applications. Thus, outsourcing pesticide application and in-house mechanized spraying are potentially endogenous.

Outsourcing pesticide application may complement or substitute in-house pesticide application. The two are interdependent and thus should be modelled jointly. Although approaches, such as propensity score matching (De Los Rios, 2022; Zhong & Peng, 2022) and endogenous switching regression model (Ankrah Twumasi et al., 2021; Khanal et al., 2018), have been widely utilized to address endogeneity, they can only consider one binary treatment variable in each estimation. This study employs a two-step control function approach to estimate the impacts of how farmers apply pesticides on pesticide expenditure by jointly modelling two binary endogenous treatment variables (i.e. outsourcing pesticide application and in-house mechanized spraying).

3.2.2 Control function approach

The control function approach proposed by Wooldridge (2015) has been widely applied in the literature (Aina & Sonedda, 2022; Johnsson & Moon, 2021; Lin & Okyere, 2021). It lends itself well to jointly modelling two endogenous treatment variables. In the first stage, two dichotomous variable functions, one each for outsourcing pesticide application and in-house mechanized spraying, are estimated as follows:

$$OS_i^* = X_i\alpha_1 + IV_i\alpha_2 + \zeta_i,\ \ OS_i = \begin{cases} 1 \ \mathit{if}\ OS_i^* > 0 \\ 0 \ \ \mathit{otherwise} \end{cases} \quad (1a)$$

$$IH_i^* = X_i\beta_1 + \eta_i,\ \ IH_i = \begin{cases} 1 \ \mathit{if}\ IH_i^* > 0 \\ 0 \ \ \mathit{otherwise} \end{cases} \quad (1b)$$

where OS_i^* represents the probability that household i chooses to use outsourcing pesticide application, and it is observed by the binary variable OS_i ($OS_i = 1$ for outsourcing service users and $OS_i = 0$ for non-users). Similarly, IH_i^* represents the propensity that the same household i chooses to use in-house machines for pesticide application, and it is also observed by the binary variable IH_i ($IH_i = 1$ for in-house machinery users and $IH_i = 0$ for non-users). X_i is a vector of control variables (e.g. age, sex, educational levels, household size, farm size, and distance). α_1, α_2 and β_1 are parameters to be estimated; ζ_i and η_i are error terms; IV_i refers to the instrumental variable (IV) used to identify the model.

Identifying a valid instrumental variable is always a challenging task. However, the IV must be statistically valid and theoretically appropriate for deriving reliable estimates. Because the questionnaire does not offer an IV that meets these criteria, we follow previous studies (Zheng et al., 2021; Zhu et al., 2020) and synthesize an IV. The synthesized IV represents the number of people using outsourcing machinery services (excluding the respondent) in the county. It affects only the farmers' decisions to outsource pesticide application; however, it does not directly affect the volume of pesticides applied and thus pesticide expenditure. Furthermore, the falsification test (Table A1 in the Appendix) confirms the statistical validity of the IV.

The conditional mixed process (CMP) model can be used to jointly estimate Equations (1a) and (1b) (Baum, 2016). The joint estimates generate a correlation coefficient of error terms, i.e. $\rho_{\zeta\eta}$. A positive sign of $\rho_{\zeta\eta}$ suggests that farmers' decisions to use outsourcing machinery services and in-house machines for pesticide applications are complements, whereas a negative sign suggests they are substitutes (Ma, Abdulai, et al., 2018; Thuo et al., 2014). Equations (1a) and (1b) help predict the probabilities that a household chooses to use outsourcing machinery services and in-house machines for pesticide applications.

In the second stage of the control function approach, we estimate the pesticide expenditure equation using an ordinary least square regression model. The empirical specification is as follows:

$$PE_i = \widehat{OS}_i\delta_1 + \widehat{IH}_i\delta_2 + X_i\delta_3 + \varepsilon_i \tag{2}$$

where PE_i measures the observed value of pesticide expenditure of household i, measured at yuan/mu; $\widehat{OS}_i$ and $\widehat{IH}_i$ are predicted outsourcing pesticide application variable and in-house mechanized spraying variable, respectively. They account for the endogeneity (Wooldridge, 2015), generating unbiased estimates. X_i is as defined earlier. δ_1, δ_2 and δ_3 are parameters to be estimated, and ε_i is the error term.

4. Data and descriptive statistics

This study uses rural household data from the 2020 CLES conducted by Nanjing Agricultural University, Nanjing, China. The collected information refers to the production in 2019. The 2020 CLES is a survey, designed specifically for Jiangsu province, that collects socioeconomic information on rural households. It was implemented in all 13 prefecture-level cities of the province using a three-stage probability proportional to size (PPS) sampling procedure. In the first stage, two counties were randomly chosen from each prefecture-level city of the province. Next, two villages or communities within each sampled county were randomly selected. In the third stage, around 50 rural residents from each sampled village or community were randomly selected and interviewed. As a result, the 2020 CLES generated a total sample of 2,600 rural households.

We cleaned the data in four steps. First, we retained only the 949 sampled households engaged in rice cultivation because this study focuses on rice producers' pesticide use behaviours. Next, we dropped eight households that outsourced pesticide application *and* used mechanized equipment in-house machines to spray pesticides, resulting in 941 observations. Third, we dropped observations with missing values, leaving 857 observations. Lastly, we used Z-scores to detect outliers and removed another ten observations.[2] In the end, 847 valid observations were used in our analysis. Among them, 99 households used outsourced pesticide application, 250 of them used mechanized equipment in-house for pesticide application; the remaining 498 households used manual sprayers to apply pesticides.[3]

Table 1 presents the descriptive statistics of the selected variables. It shows that the average pesticide expenditures per mu and kilogram rice outputs were 106 and 0.19 yuan, respectively. The rice yield is 567 kg/mu on average. In our sample, about 12% of the households outsourced machinery services, and 30% used mechanized equipment in-house to apply pesticides. This suggests that mechanized pesticide application remains low in Jiangsu province. The average age of farmers was 60 years, and around 70% of them were male. Most farmers in Jiangsu province reside in small households, with an average household size of 3.4 people. The average farm size was 11 mu (1mu = 1/15 ha). Around 34% of households reported experiencing natural disasters (e.g. crop pests or diseases) in rice production in 2019.

5. Empirical results

5.1 Factors affecting outsourcing pesticide application and in-house mechanized spraying

Although the main focus of this paper is on examining how outsourcing pesticide application and in-house

Table 1. Variable definitions and descriptive statistics.

Variables	Definition	Mean	S.D.
Dependent variables			
Pesticide expenditure per unit of area	Total pesticide expenditure per unit of area in rice production (100 yuan/mu) [a]	1.06	0.61
Pesticide expenditure per unit of rice output	Total pesticide expenditure per unit of rice output (yuan/kg)	0.19	0.11
Rice yield	Rice output (100 kg/mu)	5.67	0.99
Treatment variables			
Outsourcing pesticide application	1 if household outsources pesticide application, 0 otherwise	0.12	0.32
In-house mechanized spraying	1 if household sprays pesticides using mechanized equipment in-house, 0 otherwise	0.30	0.46
Independent variables			
Age	Age of household head (HH) (years)	60.10	10.16
Age-squared/100	Age of HH in square form (100 years)	37.15	11.89
Sex	Sex of HH: 1 if male, 0 otherwise	0.70	0.46
Primary school or below	1 if the educational level of HH is primary school or below; 0 otherwise	0.45	0.50
Junior middle school	1 if the educational level of HH is junior middle school; 0 otherwise	0.40	0.49
Senior high school or above	1 if the educational level of HH is a senior middle school or above; 0 otherwise	0.15	0.36
Risk-averse	1 if HH is risk-averse, 0 otherwise	0.73	0.45
Household size	Number of people residing in a household	3.45	1.68
Housing area	Housing area of respondent (100 square meters/capita)	0.63	0.53
Farm size	The total area of land for rice production (mu)	11.02	31.50
Natural disaster	1 if household experiences crop pests and/or diseases in rice cultivation in 2019, 0 otherwise	0.34	0.48
Subsidy	Total planting subsidies received by household (1,000 yuan)	4.54	16.34
Distance	Distance from household's largest plot to the nearest cement road (km)	0.60	0.47
Northern	1 if household is located in the northern region of Jiangsu province, 0 otherwise	0.50	0.50
Central	1 if household is located in the central region of Jiangsu province, 0 otherwise	0.30	0.46
Southern	1 if household is located in the southern region of Jiangsu province, 0 otherwise	0.20	0.40
Instrument	Number of people outsourcing pesticide application (excluding the respondent) in the sample of a county	5.43	4.89
Sample size		847	

Note: S.D. refers to standard deviation. [a] Yuan is a Chinese currency; 1 mu = 1/15 ha.

machinery use for pesticide application affect pesticide expenditure, it is instructive to first briefly discuss the factors affecting the likelihood of households pursuing the two options. To this end, we use the CMP model and present the results in Table 2. The correlation between the error terms, $\rho_{\zeta\eta}$, is statistically significant. This indicates that farmers' decisions to outsource or use in-house mechanized equipment for pesticide application are not mutually exclusive; instead, the decisions are made simultaneously (Thuo et al., 2014; Wooldridge, 2015). This stands to reason, as the two approaches can substitute one another. Our sample shows that they indeed do, with only eight households using both. This is also corroborated by the negative sign of $\rho_{\zeta\eta}$, suggesting that farmers indeed substitute between the two. Thus, separately estimating Equations (1) and (2) would generate biased estimates; the CMP approach, on the other hand, allows us to estimate the two equations jointly.

Table 2 presents the results obtained from the CMP approach. First, we consider the coefficients in column 2, showing the association between different variables and the likelihood of outsourcing pesticide application. The coefficient of age is negative and significant while that of age-squared is positive and insignificant, suggesting a 'U-shaped' relationship between age and the likelihood of outsourcing pesticide application; the turning point occurs at 64 years. That is to say that for farmers younger than 64 years, an increase in age reduces the probability of outsourcing pesticide application, whereas, for those older than 64 years, it increases the likelihood of the same. The coefficient of farm size is positive and significant – an increase in land used for rice production is associated with a rising likelihood of outsourcing pesticide application. Spraying large farms with pesticides is labour and time-intensive, especially in the absence of commercial-grade equipment, which many farmers cannot afford. Thus, they may be

Table 2. Determinants of outsourcing pesticide application and in-house mechanized spraying: CMP model estimates

Variables	Outsourcing pesticide application (0/1)	In-house mechanized spraying (0/1)
Age	−0.082 (0.047)*	0.007 (0.041)
Age-squared/100	0.064 (0.041)	−0.010 (0.036)
Sex	0.239 (0.157)	−0.199 (0.114)*
Junior middle school	0.188 (0.138)	−0.033 (0.111)
Senior high school or above	0.230 (0.182)	0.048 (0.151)
Risk-averse	0.100 (0.132)	0.072 (0.106)
Household size	−0.047 (0.039)	−0.065 (0.032)**
Housing area	0.040 (0.107)	−0.410 (0.108)***
Farm size	0.005 (0.002)***	−0.005 (0.002)***
Natural disaster	0.065 (0.124)	0.043 (0.098)
Subsidy	−0.006 (0.003)*	0.024 (0.007)***
Distance	−0.106 (0.080)	−0.024 (0.016)
Northern	−0.254 (0.144)*	0.156 (0.113)
Southern	0.020 (0.165)	0.136 (0.139)
Instrument	0.035 (0.010)***	
Constant	0.955 (1.360)	−0.174 (1.196)
$\rho_{\zeta\eta}$	−0.933 (0.090)***	
Log-likelihood	−726.275, $p = 0.000$	
Wald χ^2 (df = 29)	88.71	
Observation	847	847

Note: Robust standard errors in parentheses. The reference education level is primary school or below. The reference region is the central region of Jiangsu province. ***<0.01, **<0.05, and *<0.10.

more likely to outsource such tasks. Furthermore, farmers cultivating large areas may receive bulk discounts, thus reducing the per mu cost of spraying pesticides. These results are consistent with Baiyegunhi et al. (2019) and Cai and Wang (2021) who studied data from South Africa and China, respectively. They reported a positive link between farm size and the likelihood to outsource pest control services in the two regions, that is, farmers cultivating large farm sizes are more likely to outsource pesticide application and crop-disease management tasks in South Africa and China.

Also, there are regional differences in the likelihood of outsourcing. Farmers in northern Jiangsu are less likely to outsource than those in the central region, signifying spatial fixed effects in opting to outsource. The agricultural input markets in northern Jiangsu, the least-developed part of the province, are not mature. Farmers in this region do not have easy access to agricultural service providers. Western China is the national analog of northern Jiangsu. Compared with central and eastern China, western China (the country's least-developed region) has the lowest level of agricultural mechanization (Zhou et al., 2020a). Our results highlight the importance of considering spatial heterogeneity when designing policies and programs to promote agricultural mechanization. The coefficient of the IV is positive. This suggests that the number of farmers living in the same county who outsource pesticide application is positively associated with the likelihood of outsourcing pesticide application. This may be due to positive word-of-mouth regarding using professional services to spray pesticides, peer pressure, imitative land-use behaviours, or competition.

The last column of Table 2 illuminates the association between the control variables and the likelihood of using in-house machines for pesticide application. The significant and negative coefficient of the sex variable suggests that relative to households with female heads, those with male heads are less likely to use in-house machines for pesticide application. The coefficient of household size is negative and statistically significant. The finding suggests that larger households are less likely to use in-house machines for pesticide application. Households with more members may have high dependency ratios and thus lower per capita income available, making them less likely to own agricultural inputs and equipment such as power sprayers. The negative relationship between household size and using farm machinery has also been reported in the literature (e.g. Zhou et al., 2020).

The significant and negative coefficient of the housing area suggests that households with larger houses are less likely to spray pesticides on their own. The last column of Table 2 shows the coefficient of farm size is negative and statistically significant, suggesting that larger farms are associated with a lower probability of using in-house machines for spraying pesticides. This finding contradicts those of Belton et al. (2021), who found that farm size was positively associated with the ownership of in-house machines in India. There are marked differences between agricultural input prices in China and India. These prices have surged in China, making farmers hesitant to purchase agricultural machines (Qiu & Luo, 2021). The subsidy variable has differentiated impacts on machinery use. Our findings suggest that a higher level of subsidies received by farmers is associated with a higher probability of using household-owned mechanized equipment but a lower likelihood of outsourcing pesticide application. Subsidies induce households to purchase their own machines at lower prices, reducing their incentives to outsource pesticide application.

5.2 Factors affecting pesticide expenditure

Table 3 presents the results reporting the factors determining pesticide expenditure. To be clear, we account for potential endogeneity by using the predicted values of outsourcing machinery-intensive tasks and in-house machinery use, obtained from the first step of the control function approach (Equations (1a) and (1b)). The results show that outsourcing pesticide application significantly reduces pesticide expenditure. In contrast, in-house machinery use significantly increases pesticide expenditure. Specifically, our estimates indicate that outsourcing pesticide application reduces pesticide expenditure by about 81 yuan per mu; in-house machinery use increases the same by 118 yuan per mu. Thus, outsourcing would reduce pesticide expenditure on an 11 mu (i.e. average farm size reported in Table 1) rice farm by approximately 891 yuan – this is a considerable reduction in the cost of producing rice. This result does not accord with those of Kaiser and Burger (2022), who found that outsourcing increased Swiss farmers' pesticide expenditure, as outsourcing involves high fixed costs in Switzerland.

The negative coefficient of age and a positive coefficient of age-squared suggest that pesticide expenditure is negatively related to age for farmers younger than a specific threshold (i.e. 57.6 years) and positively correlated with age for those older than the same. Farmers gain more experience as they age, which helps them optimize pesticide use and lower pesticide expenditure. However, older farmers, say, in their 60s and 70s, may be steeped in outdated farming methods and less likely to adopt tools and techniques to help optimize pesticide use and expenditure. A lack of knowledge coupled with a reluctance to adopt modern farm management practices (e.g. spraying pesticides with machines) potentially contributes to higher pesticide expenditure among older farmers. A larger housing area is associated with a higher pesticide expenditure. A larger housing area, ceteris paribus, may denote household wealth, and wealthier households have the wherewithal to spend more on pesticides. Thus, a positive association between housing area and pesticide expenditure stands to reason.

Expectedly, the coefficient of farm size is positive, suggesting that farmers cultivating larger farms spend more on pesticides. Aida (2018) reported similar results for the Philippines. An increase in agricultural subsidies is associated with lower pesticide expenditure. China's government has implemented a 'Green Pest Control' subsidy program that may help reduce pesticide use. Wang et al. (2020b) have also reported that subsidies for crop production motivate farmers to adopt non-chemical pest management practices such as using solar light traps and paper bag traps, helping reduce pesticide use. Nevertheless, it bears emphasis that while the result is statistically significant, the magnitude of the coefficient is minuscule, suggesting that the effect is negligible in practice. The results show that a 1,000 yuan increase in subsidies reduces pesticide expenditure by a meagre of 0.9 yuan per mu. With an average farm size of 11 mu, this amounts to 9.9 yuan per farm. The distance of the farm from the nearest cement road is positively associated with pesticide expenditure. Not having ready access to cement roads makes it challenging for farmers to commute to their farms to spray pesticides. Thus, farmers may spray pesticides heavily to reduce the frequency of visits to the farm while carrying pesticides and other requisite equipment. Relative to farmers producing rice in the central region of Jiangsu, those in the north spend less on pesticides. The spatial differences potentially stem from the variations in climatic conditions and the occurrence of pest infestations across regions.

Table 3. Impact of outsourcing pesticide application and in-house mechanized spraying on pesticide expenditure per unit of area: OLS model.

Variables	Pesticide expenditure per unit of area (100 yuan/mu)
Outsourcing pesticide application (predicted)	−0.806 (0.427)*
In-house mechanized spraying (predicted)	1.183 (0.414)***
Age	−0.040 (0.022)*
Age-squared/100	0.034 (0.018)*
Sex	0.021 (0.063)
Junior middle school	0.087 (0.055)
Senior high school or above	0.039 (0.066)
Risk-averse	−0.009 (0.051)
Household size	0.010 (0.014)
Housing area	0.091 (0.047)*
Farm size	0.003 (0.001)***
Natural disaster	0.014 (0.041)
Subsidy	−0.009 (0.002)***
Distance	0.006 (0.002)***
Northern	−0.129 (0.049)***
Southern	0.021 (0.074)
Constant	1.851 (0.710)***
Observation	847

Note: Robust standard errors in parentheses. The reference education level is primary school or below. The reference region is the central region of Jiangsu province. ***<0.01 and *<0.10.

5.3 Additional findings

We have shown that outsourcing pesticide application considerably reduces pesticide expenditure per unit of area. We also analyze the effects of outsourcing machinery-intensive tasks and in-house machinery use for pesticide applications on pesticide expenditure per unit of output. The results in Table 4 show that outsourcing reduces pesticide expenditure by around 0.18 yuan per kilogram of rice produced. On the other hand, in-house machinery use increases pesticide expenditure per kilogram of output by 0.14 yuan. Given that the average farm size and rice yield are 11 mu and 567 kilograms per mu (see Table 1), respectively, our estimate suggests that outsourcing pesticide application will reduce pesticide expenditure by approximately 873 yuan for an average farm. Although not identical, this figure is in the neighbourhood of the one derived from the pesticide expenditure per mu in Table 3. The results are broadly consistent.

Lastly, we examine the effects of outsourcing pesticide application and completing the task in-house using mechanized equipment on rice yield. The results presented in Table 5 show that pesticide application through outsourcing and using in-house mechanized equipment improves rice yield by around 40 kilograms per mu and 37 kilograms per mu, respectively. More importantly, the improvements are evident regardless of applying pesticides using in-house machines or outsourcing the task. Nevertheless, the latter is associated with a larger increase in rice yield. This result chimes with the narrative above: outsourcing pesticide application reduces pesticide expenditure per unit of land and output; it also increases rice yield. These results endorse outsourcing pesticide application on all three accounts. Regardless of outsourcing or in-house application of pesticides using machines, rice yield increases. Our findings are supported by Sun et al. (2018) and Zhou et al. (2020), who study rice and maize yield in China, respectively.

Table 4. Impact of outsourcing pesticide application and in-house mechanized spraying on pesticide expenditure per unit of rice output: OLS model.

Variables	Pesticide expenditure per unit of rice output (yuan/kg)
Outsourcing pesticide application (predicted)	−0.177 (0.076)**
In-house mechanized spraying (predicted)	0.139 (0.079)*
Control variables	Yes
Constant	0.351 (0.124)***
Observation	847

Note: Robust standard errors in parentheses. ***<0.01, **<0.05, and *<0.10.

Table 5. Impact of outsourcing pesticide application and in-house mechanized spraying on rice yield: OLS model.

Variables	Rice yield (100 kg/mu)
Outsourcing pesticide application (predicted)	0.401 (0.239)*
In-house mechanized spraying (predicted)	0.373 (0.173)**
Age	0.001 (0.006)
Age-squared (100)	0.001 (0.005)
Sex	0.036 (0.035)
Junior middle school	0.017 (0.028)
Senior high school or above	0.042 (0.022)*
Risk-averse	−0.051 (0.021)**
Household size	0.010 (0.008)
Housing area	0.055 (0.022)**
Farm size	−0.000 (0.001)
Natural disaster	−0.074 (0.031)**
Subsidy	−0.001 (0.001)
Distance	0.002 (0.001)**
Northern	−0.039 (0.023)*
Southern	−0.034 (0.021)
Constant	1.459 (0.194)***
Observation	847

Note: Robust standard errors in parentheses. Rice yield is measured at log-transformed form The reference education level is primary school or below. The reference region is the central region of Jiangsu province. ***<0.01, **<0.05, and *<0.10.

6. Conclusions and policy implications

Although pesticides have been a boon for agricultural production, reducing crop losses, increasing productivity, preventing vector diseases, and improving food quality, they have also been linked to environmental degradation, adverse effects on human health, and biodiversity loss. Increased pesticide use also exacerbates climate change. And climate change itself is contributing to the pesticide resistance of pests. Farmers often resort to overusing pesticides to cope with this, thus compounding climate change and pest resistance. Breaking this vicious cycle is an important challenge of our time. Pesticide overuse is also monetarily wasteful. However, farmers often lack the knowledge and resources to optimize pesticide application to reduce their cost of production while also increasing crop yield and farm revenue. Using the control function approach to address the endogeneity issues, we explore how outsourcing pesticide application and using mechanized equipment for spraying pesticides in-house machinery affect pesticide expenditure and crop yield, using data collected from rice farmers in Jiangsu, China.

The results showed that outsourcing significantly decreases pesticide expenditure while in-house machinery use significantly increases it. Specifically, farmers who outsource pesticide application can reduce pesticide expenditure by approximately 81 yuan/mu and increase rice yield by 40 kg/mu. In comparison, although in-house spraying using mechanized equipment increases rice yield, it increases pesticide expenditure as well. Analyzing the effects of socioeconomic and demographic factors affecting pesticide expenditure, we found that it is positively associated with farm size and housing area and shares a U-shaped relationship with age, with the turning point occurring at 57.6 years. Farmers receiving subsidies spend less on pesticides. The results also point to significant regional differences in pesticide expenditure. Furthermore, farmers either outsource pesticide applications or use in-house machines for pesticide applications – they substitute one for another.

These results have important policy implications. Given that Jiangsu province is a microcosm of China in terms of agricultural mechanization and pesticide application, the results of this study apply to other provinces in China. Our results indicate that farmers who spray pesticides using mechanized equipment in-house spend more on pesticides than those who outsource pesticide application. This result is suggestive. Should farmers who spray pesticides themselves outsource this task, pesticide use may fall, leading to environmental, financial, and health benefits. Unforming farmers of the financial, health, and environmental benefits of outsourcing pesticide application is critical to increasing the adoption of commercial pest control services – awareness initiatives should be designed to this end. Also, data show a lack of pest management service providers in Jiangsu. Only 12% of households in our sample have used outsourcing services. Thus, providing financial, educational, and training support to help people set up pest management businesses is important for improving farmers' access to commercial pesticide application services. At the same time, farmers should be incentivized to outsource pesticide applications. Simultaneously addressing the demand for and the supply of pest management services would increase adoption while keeping prices in control. Targeted initiatives should be designed to encourage older farmers (i.e. those above 58 years) to outsource pesticide application.

Moreover, the negative association between farm size and in-house mechanized spraying suggests that not only do large farming operations benefit from economies of scale, but they also tend to spend less on pesticides per unit of land. Strategies promoting the aggregation of smallholder farms, for example, through changes to land transfer regulations, may contribute to lowering pesticide use. Farmers in northern Jiangsu, the least-developed region in Jiangsu province, are the least likely to outsource pesticide application. Interventions should be designed specifically to appeal to the farmers in less developed regions (i.e. northern Jiangsu and western China) to encourage them to outsource pesticide application. Jiangsu province and the country as a whole should allocate more resources to improving agricultural input markets in these areas to enhance farmers' access to outsourcing agricultural machinery services.

Lastly, we discuss some limitations of this study. First, farmers may outsource farming activities to government agricultural machinery service agencies, combined services enterprises, family farms, or individual farmers who own agricultural machines. This choice determines the effectiveness and impact of pesticide application. One group of agencies may be systematically better than others. However, the dataset used in this study does not provide any information about service providers, limiting our abilities to explore the potential heterogeneous effects of outsourcing pesticide application. Second, we capture farmers' binary decisions to outsource machinery-intensive tasks and spray pesticides in-house using mechanized equipment due to data limitations. This only partially addresses the relationship between these two approaches to pesticide application. Therefore, when relevant data are available, future studies should explore how different sources of outsourcing services and intensities of outsourcing and in-house machine use affect pesticide consumption in China. These analyses can also be applied to other countries seeking to reduce the use of pesticides and improve economic and environmental sustainability. Third, we did not analyze the effects of agricultural machinery on the intensity of pesticide use, as the 2020 CLES does not have the requisite information. It would be valuable to understand how agricultural machinery affects the intensity when the data become available.

Notes

1. No household in our sample rented equipment for pesticide application.

2. Introduction to Z-scores: https://statisticsbyjim.com/basics/outliers/
3. It is worth to noting here that, in China, almost all farmers have used different levels of pesticides in farm production. This is different from some African countries, where some farmers do not use pesticides in farm production (Abebaw & Haile, 2013).

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Data availability statement

The data that support the findings of this study are available from Junpeng Li upon request.

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Appendix

Table A1. Falsification tests of the instrumental variable's validity.

Variables	*F*-value	*p*-value
Pesticide expenditure per unit of area	0.62	0.438
Pesticide expenditure per unit of rice output	2.19	0.152
Rice yield	2.67	0.115
Outsourcing pesticide application	$\chi^2 = 23.40$***; $p = 0.000$	

Note: Pesticide expenditure per unit of area and pesticide expenditure per unit of output are measured in 100 yuan/mu and yuan/kg, respectively. Rice yield is measured in log-transformed form. ***<0.01.