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Impact of specialized agricultural services on climate-smart agricultural practices: Evidence from biopesticide application in Jiangsu Province, China

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ABSTRACT

Global climate change is aggravating the occurrence of pests and diseases, however, pesticide residue caused by the abuse of chemical pesticides is emerging as a worldwide issue with a great threat to the ecological environment, human health, and food security. Biopesticide application, a component of climate-smart agricultural practices, is viewed as a vital alternative for agricultural sustainable development. Due to the additional cost attached to externalities and information insufficiency, the adoption rates of biopesticide are still quite low in most developing countries. By using panel data of 3143 rural households from 2020 to 2021 in Jiangsu Province, this paper builds a theoretical framework of whether and how specialized agricultural service (SAS) for specialized pest control affects farmers' biopesticide application, and then employs an Endogenous Switching Probit model to verify this effect and its channels empirically. The empirical results show that the SAS purchase can increase significantly the probability of smallholders' biopesticide adoption by 30.8%. Without consideration of the self-selection bias, this probability would drop to 16.2%. The potential channels of the SAS influencing farmers' biopesticide application are technology popularization (training) and machinery substitution resulting from SAS. Moreover, our findings also indicate that the effects of SAS on biopesticide adoption are heterogeneous, and vary with farmers' education level, cooperative members, and land size. This paper provides the first empirical evidence for the effect of SAS on biopesticide promotion, which is expected to contribute to agricultural sustainable development and food safety in most developing countries.

1. Introduction

In the context of global climate change aggravating the occurrence of pests and diseases, chemical pesticides play a vital role in pest control and disease reduction, and grain yield increase (Bagheri et al., 2019; Huang et al., 2003; Mazhar et al., 2021). In China, about 80 million tons of grain loss were averted from pesticide inputs in 2019 (Ministry of Agriculture of China, 2020). However, with high toxicity and residues, the overuse of pesticides has also posed a serious threat to food safety, human health, and ecological diversity in most developing countries, especially China (Finizio and Villa, 2002; Garming and Waibel, 2009; Mahmood et al., 2016;). The unit input of pesticides for Chinese farmers was 9.95 kg/ha, which was about 4 times the global average in the same period.[2] Unfortunately, only 30% of pesticides act directly on pests and diseases, the remaining 70% drain into soil, water, and air, which leads to terrible negative externalities (Tang and Luo, 2021).

Designed as a substitute for chemical pesticides, biopesticide application, a component of climate-smart agricultural practices (CSAPs),[3] is becoming increasingly popular all over the world (Hakala et al., 2011; Mazhar et al., 2021). Biopesticides are usually extracted from natural organisms and have outstanding technical features, like low residue, low toxicity, and pro-environment, which can alleviate the pollution of cultivated land and contribute to food safety (Huang et al., 2022; Srinivasan et al., 2019). Given these features, Damalas and Koutroubas

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[2] Data Source: https://www.fao.org/faostat/zh/#data and http://www.stats.gov.cn/tjsj./ndsj/.

[3] CSAPs include practices and technologies that have the potential to achieve the "triple-win" of increasing incomes, food security, climate change adaptation and mitigation (FAO, 2017).

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(2018) predicted that the global market for biopesticides would outpace that of chemical pesticides by the 2050s, with annual growth rates of 10% -15%. However, it is also argued that some drawbacks of biopesticides, such as additional skill requirements and higher application costs, are the major obstacle to rapid promotion in Africa and Asia (Damalas and Koutroubas, 2018; Tang and Luo, 2021). Currently, the market share of biopesticides in China is just about 10% which is much lower than other developed countries with a 20% - 60% market share (Guo et al., 2019; Huang et al., 2022). Therefore, the research on farmers' biopesticides adoption behavior or the channels of encouraging smallholders to adopt biopesticides will make sense for the effective promotion of biopesticides.

Fruitful empirical studies have focused on farmers' biopesticide adoption behavior, which mainly explored the influencing factors on biopesticide adoption from three broad directions regarding farmers, markets, and government. Among the factors derived from farmers, the insufficient knowledge and extra cost of biopesticides can result in biased cognition and effectiveness underestimation that discourage risk-averse farmers from adopting biopesticides (Pray and Nagarajan, 2012; Tang and Luo, 2021). However, Abdollahzadeh et al. (2018), Li et al. (2022), and Yu et al. (2019) confirmed that education, income, environmental attitude, and land size can counteract this inhibitory effect. Moreover, Liu et al. (2022) and Zhang and Liu (2020) also revealed that joining the cooperatives plays an important role in biopesticides knowledge transfer and application service supply. Regarding the imperfect market of biopesticides, the added value of agricultural products applying biopesticides is usually not approved by potential customers for the faulty product traceability system, which is named the 'Lemon Market' (Kaur et al., 2023; Luo et al., 2020). Bagheri et al. (2021) and Luo et al. (2020) showed that pesticide labels and market access can be suitable channels to make up for the lack of market regulation. For the factors from the side of government, some studies found that agricultural extension, subsidies, and insurance significantly influenced farmers' biopesticides adoption behavior (Tang and Luo, 2021; Wuepper et al., 2021). In most developing countries, biopesticide promotion activities are mainly the responsibility of the public extension department, however, its effectiveness is limited due to the poor connection with smallholders (Damalas and Koutroubas, 2018; Huang et al., 2022).

By contrast, since specialized agricultural service (SAS) can provide specialized services covering pre-production, in-production, and post-production to smallholders, the SAS has been viewed as a bridge effectively connecting smallholders with major factor markets in China (Yang et al., 2013; Zhang et al., 2017). Independent of land scale, SAS based on the division of labor can achieve economies of scale in a roundabout way with a better combination of machinery, labor, and other factors (Picazo-Tadeo and Reig-Martínez, 2006; Yang et al., 2013). And SAS has been reported to significantly improve agricultural productivity and farm income (Baiyegunhi et al., 2019; Picazo-Tadeo and Reig-Martínez, 2006), promoted non-agricultural employment (Lu and Gao, 2020; Sun et al., 2018; Zhang et al., 2017), reduced production risk (Qiu and Luo, 2021; Yang et al., 2022), and optimized the mix of production factors (Lu et al., 2021; Sun and Liu, 2019). As an emerging pro-environmental technology in CSAPs, biopesticide not only makes sense for agricultural sustainable development, but also human health (Kumar et al., 2021; Tang and Luo, 2021). Hence, whether and how the purchase of SAS for specialized pest control promotes the application of biopesticide are problems worth further discussing for food safety and agriculture sustainability, which is insightful for policymakers.

Given the unclear relationship between SAS and biopesticide adoption, this study utilizes the panel data from 2020 to 2021 at the plot level of 3143 rural households in Jiangsu Province, China, and applies an endogenous switching probit (ESP) model to explore the influence of the SAS on biopesticide adoption and its potential influence channels. To the best of our knowledge, there are few studies have explored the impact of SAS on CSAPs application, and all have focused on straw returning and organic fertilizer,[4] such as Lu et al. (2021), Wan and Cai (2022), and Yang and Zhang (2022). Compared with previous studies, our study makes the following possible contributions: First, it extends to the existing literature on the influence of SAS over CSAPs application, since the biopesticide adoption is neglected. Moreover, this is the first study exploring the influence channels between the SAS and CSAPs application with theoretical and empirical analysis, which was not covered by previous studies. Second, this study eliminates the interference of the time effect and self-selection bias by using panel data and the ESP model, while the vast majority of existing studies were conducted through cross-section data and didn't consider this bias. Third, key socioeconomic characteristics (e.g., education, cooperative members, and land size) of the sample farmers are utilized to document the evidence for the heterogeneous effects of SAS on CSAPs application. Overall, this study is expected to contribute to policymaking about CSAPs extension and provide useful experience for agricultural sustainable development and food safety in China and other developing countries, especially in the context of increased global climate change.

The remainder of this article is organized as follows. Section 2 is the literature review and theoretical framework. Section 3 introduces the empirical methods, while Section 4 gives the data description. In Section 5, we report the empirical results and related discussion. The last section is the conclusion and policy implications.

2. Literature review and theoretical framework

2.1. Literature review

Smallholders are faced with multiple climate change shocks, like floods, drought, and pests & diseases, which significantly affect agricultural productivity and food security (Chai et al., 2023; Chen et al., 2023; Mazhar et al., 2021). To adapt and mitigate climate change, CSAPs are increasingly promoted worldwide as some practices or technologies to contribute to the global agricultural transformation into more productive, environmentally friendly, and sustainable agriculture-encouraging a balanced paradigm (Aryal et al., 2018; FAO, 2017; Mazhar et al., 2021). Among various CSAPs, agroforestry, cover cropping, integrated crop-animal farming, and integrated pest management (IPM) are common practices, and have been broadly studied (Antwi-Agyei et al., 2021; Mazhar et al., 2021). However, as a typical practice of IPM, more and more scholars have paid attention to the role of biopesticides in climate-smart agriculture (Heeb et al., 2019; Palombi and Sessa, 2013; Sekabira et al., 2022).

Biopesticides are natural active agents for pest control that are extracted from biology and even certain minerals (Damalas and Koutroubas, 2018; Sagar, 1991). They can be roughly divided into microbial pesticides, agricultural antibiotics, biochemical pesticides, plant-extracted pesticides, and animal-extracted pesticides according to the source of extraction (Tang and Luo, 2021). Compared with chemical pesticides, biopesticides show a strong specificity and high activity, in other words, are relatively safe for non-targeted organisms (Uri, 1998). Biopesticides can theoretically replace chemical pesticides, though their application has positive externality and long-term benefits. As early as the 1980s - 1990s, China began to develop and register several biopesticides, such as *Wellbutrin*, *Abamectin*, and *Bacillus thuringiensis (Bt)* pesticides (Huang et al., 2022). In 2006, the Chinese government initiated a promotion project for biopesticides and then set up ten biopesticides subsidy demonstration sites in 2014, among which included Jiangsu Province. Like other CSAPs, since biopesticides have some technical risks (like high cost, unstable effectiveness, and complex application), the market share of biopesticides is just about 10% in China and only 30% of biopesticides have been effectively applied (Guo

[4] The application of straw returning and organic fertilizer are two of common CSAPs (Aryal et al., 2018; Palombi and Sessa, 2013).

et al., 2019; Zheng et al., 2022). Hence, the potential market of biopesticides cannot be underestimated, and the main uncertainty is the rates of uptake for farmers (Damalas and Koutroubas, 2018; Han et al., 2023). More detailed information about the relationship between biopesticides and CSAPs is displayed in Appendix A.

Derived from the division of labor, specialized agricultural services (SAS) can also be seen as a kind of outsourcing, that is, vertical disintegration in agricultural production (Quinn, 1992; Marshall, 1920; Smith, 1776). Generally speaking, purchasing the SAS means that a farmer contracts some or all of the production tasks to individuals or organizations that specialize in providing production services (Sun et al., 2018). The individuals always include some skilled farmers or family farms, while related organizations cover agricultural public service departments, cooperatives, collective economic organizations, and agribusinesses (Qiu and Luo, 2021). Moreover, the services these organizations provide usually involve pre-production (e.g., seed sales), in-production (e.g., tillage, fertilization and pesticide application, and harvest), and post-production (e.g., agricultural products processing). It is worth mentioning that most service providers often offer several items of service at the same time, not just one. Taking specialized pest control for example, the SAS usually provides pesticide use consulting & training services, mechanical spraying services, and others (Sun et al., 2018).

Viewed as a supplement to the public extension department, SAS has a special advantage in the supply of production factors or new technologies (Ren, 2023; Tang et al., 2018). Hence, the related official government documents[5] have proposed to enhance the supply and application of agricultural pro-environmental technologies through the SAS, which include biopesticides. As regards specialized pest control, purchasing SAS has at least two advantages over management by smallholders. First, it can help farmers overcome the increasing demand for labor and their disadvantages concerning the use of spraying machines and other plant protection machineries (Igata et al., 2008; Tang et al., 2018; Yang et al., 2013). Second, professional service organizations with specialized expertise in specialized pest control can help farmers who lack certain skills overcome their skill and knowledge constraints in pesticide use, which can reduce technology application risk and boost the efficiency of pest control (Qiu et al., 2021; Sun et al., 2018; Yang et al., 2022). Since the application of biopesticides has additional requirements for both information (knowledge) and machinery (labor), the purchase of corresponding SAS is likely to affect the adoption of biopesticides. More detailed information about SAS is shown in Appendix B.

2.2. Theoretical framework

To further understand the effect of SAS on biopesticides adoption, we construct a Technology Selection Model proposed by Just and Zilberman (1988) and Ridier et al. (2013). Assume that the smallholders face the constraints of land, capital, and labor in incomplete factor markets, and they mainly decide the adoption of agricultural technologies based on their family's initial endowment. Suppose that a householder owns farmland (S), labor (L), and capital (K), where the farmer applies chemical pesticides in farmland (S_0) and biopesticides in farmland (S_1),[6] so $S_0 + S_1 = S$. The profit per unit area applying chemical pesticides ($\widetilde{\pi_0}$) and biopesticides ($\widetilde{\pi_1}$) are as follows:

$$\begin{cases} \widetilde{\pi_0} = \pi_0 + \varepsilon_0 \\ \widetilde{\pi_1} = \pi_1 + \varepsilon_1 \end{cases} \tag{1}$$

Where ε_0 and ε_1 are the random interference of profit per unit area under the chemical pesticides and biopesticides adoption respectively. The means of $\widetilde{\pi_0}$ and $\widetilde{\pi_1}$ are $E(\widetilde{\pi_0}) = \pi_0$ and $E(\widetilde{\pi_1}) = \pi_1$, and the variances are $V(\widetilde{\pi_0}) = \sigma_0^2$ and $V(\widetilde{\pi_1}) = \sigma_1^2$. We assume that the uncertainty of output under biopesticides is greater than that under chemical pesticides, that is, $\sigma_1^2 > \sigma_0^2$.

Suppose that farmers consider profit and risk comprehensively when making production decisions and pursue utility maximization, we use a Mean-Variance approach[7] to solve the maximization problem:

$$max\ EU = E(\widetilde{\pi_0}S_0 + \widetilde{\pi_1}S_1) - \frac{1}{2}\varnothing V(\widetilde{\pi_0}S_0 + \widetilde{\pi_1}S_1) \tag{2}$$

$$\text{s.t.}\ l_0S_0 + l_1S_1 \le L, k_0S_0 + k_1S_1 \le K \tag{3}$$

Where $\varnothing$ represents the producer absolute risk aversion index or Arrow-Pratt of absolute risk aversion index,[8] and $\varnothing = -EU''/EU'$. l_0 and l_1 are the demands of labors per unit area applying chemical pesticides and biopesticides, while k_0 and k_1 are the demands of capital per unit area respectively. Expanding the variance in Eq. (2) and considering the constraint conditions (Eq. (3)), the Lagrange method is used to calculate the extreme value, and Eq. (2) is further transformed into:

$$\begin{aligned} Max\ EU = {} & \pi_0S_0 + \pi_1S_1 - \frac{1}{2}\varnothing\left[(S - S_1)^2\sigma_0^2 + S_1\sigma_1^2 + 2(S - S_1)S_1\rho\sigma_0\sigma_1\right] \\ & + \lambda_1(\mathrm{L} - l_0\mathrm{S}_0 + l_1S_1) + \lambda_2(\mathrm{K} - k_0\mathrm{S}_0 + k_1S_1) \end{aligned} \tag{4}$$

Then, by calculating the first-order condition of EU to S_1, we can derive the value of S_1 when EU gets the max value ($\frac{\partial EU}{\partial S_1} = 0$):

$$S_1 = \frac{\frac{1}{\varnothing}(\pi_1 - \pi_0) + S\sigma_0(\sigma_0 - \omega\sigma_1) - \lambda_1(l_1 - l_0) - \lambda_2(k_1 - k_0)}{\sigma_1^2 + \sigma_0^2 - 2\omega\sigma_0\sigma_1} \tag{5}$$

Where ω is the correlation coefficient of π_1 and π_0, we assume that $\omega < 0$ because one purpose of adopting a mix of chemical pesticides and biopesticides is to reduce production risk. λ_1 and λ_2 respectively represent the labor and capital constraints faced by farmers. The larger the value, the greater the constraint faced by farmers.

Inferred from Eq. (5), farmers' adoption of biopesticides is affected by two sets of factors: (*i*) The constraints of initial endowment owned by farmers, such as land and capital, as well as the degree of risk aversion for farmers. The relationship between these factors and biopesticide adoption is as follows: $\partial S_1/\partial S > 0$, $\partial S_1/\partial\lambda_1 < 0$, $\partial S_1/\partial\lambda_2 < 0$, and $\partial S_1/\partial\varnothing < 0$. (*ii*) The technical features of biopesticides, including the uncertainty about the effectiveness and the demand for labor and capital. The relationship between these factors and biopesticide adoption is as follows: $\partial S_1/\partial\sigma_1^2 < 0$, $\partial S_1/\partial l_1 < 0$, and $\partial S_1/\partial k_1 < 0$.

Combined with the existing studies for the SAS, we suppose that the SAS affects the adoption of biopesticides mainly through two channels: (*i*) Making up for the shortage of labor (λ_1) and dedicated capital (λ_2;e.g., plant protection machinery) when farmers apply biopesticides; (*ii*) Reducing farmers' risk aversion ($\varnothing$) and technology application risk (σ_1^2) for biopesticides by relevant knowledge popularization or training. Hence, we propose the hypothesis that the SAS can positively promote biopesticides adoption and will verify the above-mentioned promotion channels in the later section (Fig. 1). As some studies also pointed out that the land size can affect the farmers' decisions on SAS purchase and

[5] "Guidelines on Accelerating the Development of Agricultural Producer Services" (http://www.gov.cn/gongbao/content/2018/content_5271797.htm) in 2017 and "Suggestions on Promoting Effective Linkage between Smallholders and Modern Agricultural Development" (http://www.gov.cn/zhengce/2019-02/21/content_5367487.htm) in 2019.

[6] The specific situation of the adoption of biological and chemical pesticides by farmers in this study is placed in Appendix E.

[7] A classical method to calculate the optimal portfolio choice in the Portfolio Theory (Just and Zilberman, 1988; Ridier et al., 2013).

[8] The increase of $\varnothing$ means that farmers' risk avoidance degree is deepened (Ridier et al., 2013).

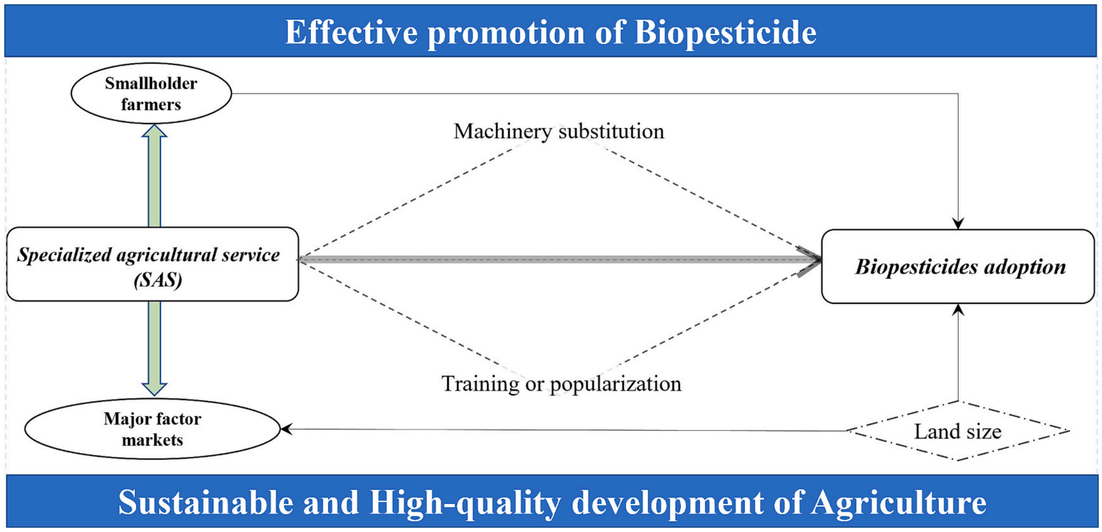

Fig. 1. Conceptual framework.

biopesticides adoption (Qiu and Luo, 2021; Tang and Luo, 2021), and $\partial S_1/\partial S > 0$ in our analytical framework, we further explore the role of land size in our study.

3. Empirical methods

To evaluate the effect of SAS on farmers' decision to biopesticides adoption, an outcome equation can be expressed as:

$$T_{it}^{*} = \alpha + \beta X_{it} + \gamma A_{it} + \mu_{it} \text{ with } T_{it} = \begin{cases} 1 \ if \ T_{it}^{*} > 0 \\ 0 \ otherwise \end{cases} \tag{6}$$

Where T_{it}^{*} (latent variable) denotes the expected net benefits of biopesticides adoption for household i in year t, a farmer would opt to adopt biopesticides (T_{it}=1) if $T_{it}^{*} = \pi_1 - \pi_0 > 0$. A_{it} represents a dummy variable that measures the SAS purchase status of farmers (purchaser = 1; non-purchaser = 0); μ_{it} is an error term. X_{it} is a vector of control variables potentially associated with smallholders' decisions in SAS purchase or biopesticides adoption. According to the relevant literature, these control variables generally include individual characteristics (e.g., age, gender, and education), household features (e.g., family labor, income, and subsidy), farm features (e.g., land size, land fragmentation, and crop variety), and region and year dummy variables (Deng et al., 2020; Picazo-Tadeo and Reig-Martínez, 2006).

3.1. The ESP model

However, applying the ordinary least squares (OLS) specification in Eq. (6) can lead to biased or spurious estimations, because farmers may self-select to purchase SAS that is influenced by some unobservable characteristics (e.g., incentives and capabilities). Moreover, it's impossible to observe the biopesticides adoption by the same peasant at the same time when purchasing SAS versus without purchasing SAS, which is also termed simultaneity bias. To address the issues of self-selection and simultaneity biases, some econometric methods, such as propensity score matching (PSM) and treatment effect model (TEM), have been widely conducted (Pan et al., 2017; Tam and Shimada, 2021). Nevertheless, the PSM method has a limitation in that it just deals with self-selection correlated with observed factors and ignores the impacts of unobserved factors, while the TEM method assumes that the influence of control variables on biopesticides adoption does not differ between SAS purchasers and non-purchasers (Tang and Luo, 2021). By contrast, the ESP method,[9] which makes up for the limitations of the above two methods, employs the full information maximum likelihood (FIML) strategy to estimate one selection and two outcome equations simultaneously (Ren et al., 2021). This method recognizes the self-selection of SAS purchase is derived from the expected benefits of SAS, and assumes that different statuses may exist between SAS purchasers and non-purchasers. Following Kumar et al. (2018), the selection equation is expressed as:

$$A_{it}^{*} = \beta X_{it} + \delta I_{it} + \theta_{it} \text{ with } A_{it} = \begin{cases} 1 \ if \ A_{it}^{*} > 0 \\ 0 \ otherwise \end{cases} \tag{7}$$

Where A_{it}^{*} (latent variable) measures the difference between the expected benefits of SAS purchasers and non-purchasers, a farmer would opt to purchase SAS ($A_{it} = 1$) if $A_{it}^{*} > 0$. X_{it} is a vector of control variables representing farmers' decisions to purchase SAS. θ_{it} is an error term following a normal distribution with zero means. Considering the selection bias, Eq. (7) incorporates an instrument variable (IV), I_{it}, that captures the peer effects for SAS purchase at the village level (i.e., village-level purchase rates of SAS except for the farmer himself). Given that the similar IV has been employed in the studies of Deng et al. (2020) and Qiu et al. (2021), the validity of this IV relies on two critical criteria: 1) this IV influences farmers' decision of SAS purchase, and 2) this IV has no direct effect on farmers' biopesticides adoption except through SAS purchase. Due to the space constraint, we show the content of the IV's validity testing in Appendix C.

Correspondingly, two regime equations are expressed to interpret the different outcomes of biopesticides adoption, which are defined as follows:

$$\text{Regime 1}: T_{1it} = \beta_1 X_{1it} + \tau_{1it} \text{ if } A_{it} = 1 \tag{8a}$$

$$\text{Regime 2}: T_{0it} = \beta_0 X_{0it} + \tau_{0it} \text{ if } A_{it} = 0 \tag{8b}$$

Where T_{1it} and T_{0it} are decisions of biopesticides adoption for SAS

[9] Although the ESP method is often used for cross-section data (e.g., Aryal et al., 2020; Sun, 2018), more and more studies have applied it in the case of panel data and have been published in international top or authoritative journals, such as Kumar et al. (2018) and Lin et al. (2022).

purchasers and non-purchasers, respectively. X_{1it}, X_{0it} are the vectors of the exogenous variables mentioned above that might influence the decisions. β_1 and β_0 denote the parameters to be estimated, while τ_{1it} and τ_{0it} is the random disturbance term. Following Miranda and Rabe-Hesketh (2006), the θ_{it}, τ_{1it}, and τ_{0it} are jointly normally distributed, and the correlation matrix is specified as:

$$\Omega = cov(\theta_{it}, \tau_{1it}, \tau_{0it}) = \begin{pmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{pmatrix} \tag{9}$$

Where ρ_0, ρ_1, and ρ_{10} indicate the correlations between τ_{0it} and θ_{it}, τ_{1it} and θ_{it}, and τ_{0it} and τ_{1it}, respectively. If $\rho_1 \neq \rho_0 \neq 0$, A_{it}, the binary categorical variable for SAS purchase, is viewed as an endogenous variable that provides a biased estimator, while ρ_{10} can't be calculated (Huang et al., 1991). Furthermore, ρ_1 and ρ_0 respectively measure the extent to which SAS influences the biopesticides adoption decision of purchasers and non-purchasers.

3.2. Treatment effects estimating

After attaining the parameters of the ESP model through the FIML strategy, the self-selection-bias corrected estimators of different treatment effect measures suggested by Caliendo and Kopeinig (2008) — average treatment effect on the treated (ATT) and average treatment effect (ATE) — are expressed as:

$$ATT = E[Pr(T_1 = 1|A = 1, X = x)] - E[Pr(T_0 = 1|A = 1, X = x)]$$

$$= E[(\Phi(\beta_1 X_1, \delta I, \rho_1) - \Phi(\beta_0 X_0, \delta I, \rho_0)/F(\delta I)] \tag{10}$$

$$\begin{aligned} ATE = E[Pr(T_1 = 1|A = 1, X = x)] - E[Pr(T_0 = 1|A = 0, X = x)] \\ = E[F(\beta_1 X_1) - F(\beta_0 X_0)] \end{aligned} \tag{11}$$

Where Φ and F represent the cumulative function of a bivariate normal distribution. $Pr(T_1 = 1|A = 1, X = x)$ and $Pr(T_0 = 1|A = 1, X = x)$ are predicted probabilities of biopesticides adoption for SAS purchasers in observed and counterfactual contexts, while $Pr(T_0 = 1|A = 0, X = x)$ represents predicted biopesticides application probabilities for service non-purchasers in the observed context. Since ATT focuses on the impact on the farmers who actually purchased SAS and ATE is based on the whole sample, the estimates of ATT could make more sense for policy-makers (Heckman, 1997). Therefore, we would mainly report the results of ATT in Section 5.3.

3.3. Mechanism analysis

To explore the channels or mechanisms underlying the influence, we further conduct a mediation analysis approach. Regarding the mediating effects, we also conduct a stepwise regression proposed by Valeri and VanderWeele (2013) to identify the causal mediating effects between SAS purchase and biopesticides adoption. First, considering the pre-treatment confounders, SAS purchase is viewed as a treatment variable or potential mediator is incorporated into Eq. (12a). Second, we regress the mediation with a specified outcome model in Eq. (12b), which covers the interaction terms between SAS purchase and potential channels.

$$M_{it} = \alpha_2 + \gamma_1 S_{it} + \gamma_2 X_{it} + \vartheta_{it} \tag{12a}$$

$$T_{it} = \alpha_3 + \gamma_3 S_{it} M_{it} + \gamma_4 S_{it} + \gamma_5 M_{it} + \gamma_6 X_{it} + \varepsilon_{it} \tag{12b}$$

Where M_{it} are the mediating variables of SAS purchase affecting biopesticides adoption, T_{it}, A_{it}, and X_{it} are the same variables in Eqs. (6) and (7), while γ represents the vector of parameters to be estimated. The variable (M_{it}) is viewed as the mediator if $\gamma_1 \neq 0$ and $\gamma_3 \neq 0$, denoting that A_{it} has a statistically significant effect on T_{it} via M_{it}.

4. Data

4.1. Data sources

Data utilized in this paper were derived from China Land Economic Survey (CLES) carried out by Nanjing Agricultural University in 2020 and 2021.[10] The two rounds of partial follow-up surveys conducted the sampling method of Probability Proportional to Size (PPS) and covered the information of villagers that covers the basic characteristics of household members, agricultural production at the plot level, factor market, and so on. Specifically, fifty-two administrative villages were chosen from thirteen prefecture-level cities of Jiangsu Province in 2020, while twelve prefecture-level cities were traced in 2021. Given that fifty villagers were randomly sampled in each administrative village, this database contains 2628 households in 2020 and 2420 households in 2021. By eliminating the outliers and missing values, we finally employed the panel data with 3143 observations, where 1608 observations are included in 2020 and 1535 observations in 2021.[11]

As a major grain-producing area of China, Jiangsu province is crossed by the Qinling Mountains-Huaihe River Line[12] and has the common characteristics of agricultural production in both southern and northern China (Fig. 2). By 2019, Jiangsu province had developed 12,697 SAS organizations, of which 6300 were dedicated to providing specialized pest control services.[13] With frequent outbreaks of diseases and insect pests, Jiangsu Provincial has invested a special fund of 15 million yuan every year to subsidize biopesticides and other plant protection materials for specialized pest control since 2012, and 26,425 tons of biopesticides were used in 2017, accounting for 35% of chemical pesticide use.[14] Hence, exploring the impact of SAS on biopesticides adoption in Jiangsu province can be a typical experience and provides useful insights into the agricultural sustainable development of China, and even other developing countries.

4.2. Variable specification

Table 1 presents the description and summary statistics of the main variables employed by our study. We use a dummy variable indicating whether farmers adopt biopesticide to measure farmers' biopesticide adoption behavior. Moreover, another dummy variable refers to whether to purchase SAS for specialized pest control is chosen as the key explanatory variable. As shown in Table 1, farmers who adopted biopesticide account for 48.5% and 44.2% of all respondents in 2020 and 2021,[15] while the proportion of farmers who purchased SAS reached 52.1% in 2020 and 42.2% in 2021. To address the issue of self-selection, the instrumental variable in this study includes the services network,

[10] Data and original questionnaire are illustrated in https://jscv.njau.edu.cn/#/index.

[11] There are 73 attritions in this panel survey, referring to the low attrition rate (4.4%), which is much lower than the 10%—20% attrition rate of other common sociological surveys at the national level of China (Liang, 2011). Moreover, since these attritions are caused by the death of some old respondents and the transfer of residence that no longer engaged in agricultural work, the issue of sample selection would not arise, because these respondents have been excluded in the population components of 2021(Bhattacharya, 2008; Hirano et al., 2001).

[12] The Qinling-Huaihe Line is the geographical dividing line between northern and southern regions in China. To the north and south of this line, there are obvious differences in natural conditions, geographical features, agricultural production or people's living customs (Liu et al., 2015).

[13] Data source: http://nynct.jiangsu.gov.cn/art/2021/3/25/art_13464_9714414.html.

[14] Data source: http://www.agroinfo.com.cn/other_detail_5081.html.

[15] The most commonly used biopesticides and the largest market share in Jiangsu Province are *Bacillus thuringiensis (Bt)* and *Validamycin*, both of which are microbial biopesticides.

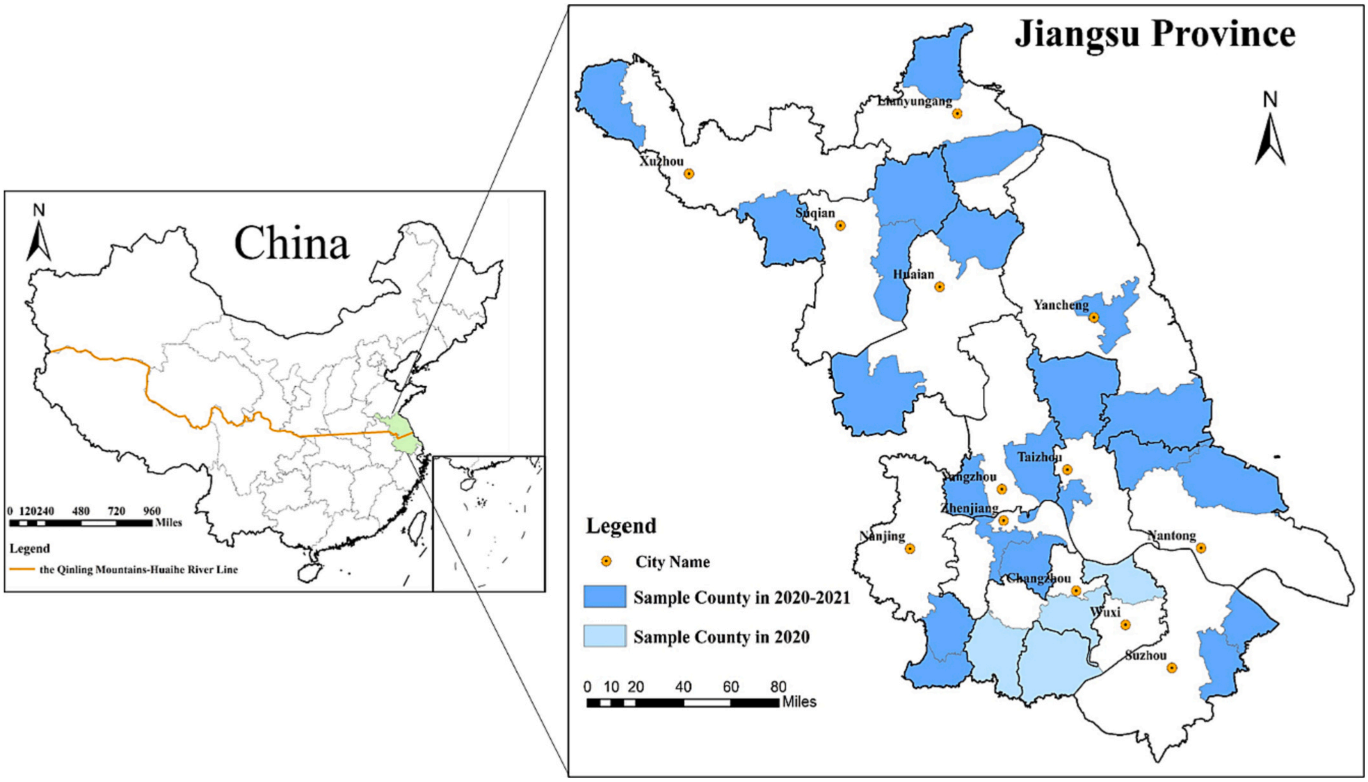

Fig. 2. Distribution of sample counties in Jiangsu Province, China.

Table 1
Description and summary statistics of variables.

Variables	Description	Year:2020		Year: 2021	
		Mean	***S.D.***	***Mean***	***S.D.***
Biopesticide adoption	1 if farmers adopted biopesticide; 0 otherwise	0.485	0.497	0.442	0.496
Specialized agricultural services	1 if farmers purchased SAS for specialized pest control; 0 otherwise	0.521	0.500	0.422	0.494
Services network (IV)	Village-level purchase rates of SAS (excluding farmer-self)	0.443	0.296	0.345	0.253
Control variables:					
Age	Age of household head (years)	61.372	10.096	62.605	10.363
Gender	1 if householder is male; 0 otherwise	0.918	0.274	0.922	0.268
Education	Education level of household head (years)	7.258	3.580	7.363	3.628
Health	Very bad = 1, bad = 2, general = 3, good = 4, excellent = 5	3.908	1.066	4.011	1.074
Risk attitude	Risk aversion =1, risk neutrality = 2, risk preference =3	1.308	0.588	1.298	0.564
Time preference	Near-sighted = 1, general-sighted = 2, far-sighted = 3	1.707	0.727	1.688	0.681
Environmental attitude	Not behaving environmentally = 1, generally = 2, behaving environmentally = 3	2.615	0.528	2.638	0.505
Income	Total family income that excludes subsidy (yuan, Log (income+1))	11.305	1.387	11.155	1.375
Subsidy	Subsidies for grain planting (yuan, Log(subsidies+1))	5.662	2.573	5.263	2.874
Agricultural labor	Number of labors involved in agricultural production	1.756	0.864	1.755	0.832
Cooperative member	1 if householder is a member of the cooperative; 0 otherwise	0.025	0.155	0.022	0.145
Land	Area of cultivated land actually operated by household (mu, Log (land+1))	1.948	1.321	1.822	1.312
Land2	Square item of cultivated land area	5.537	8.153	5.040	8.330
Land fragmentation	Ratio of land pieces to land area	1.133	3.235	1.250	2.297
Crop variety	Rice = 1 and maize = 0	0.801	0.399	0.792	0.462
Mediator variables:					
Training or popularization	1 if householder got training or introduction for biopesticide from SAS; 0 otherwise	0.334	0.472	0.345	0.476
Machinery substitution	1 if householder didn't purchase agricultural machinery but purchased related mechanical spraying services; 0 otherwise	0.337	0.188	0.327	0.469

Note: *yuan* is a Chinese currency unit (1 USD = 6.71 *yuan* on January 14th, 2023). 1 *mu* = 1/15 ha. For data smoothing, we took the logarithm of these variables such as *Income*, *Subsidy*, *Land*, and *Non-farm income*.

which refers to the village-level purchase rates of SAS (the average purchase rate was 44.3% in 2020 and 34.5% in 2021).

Regarding other control variables, this study selects 14 variables in 3 categories as control variables, including householder's individual characteristics, family characteristics, and farm features. Firstly, Age, Gender, Education, Health, Risk attitude, Time preference, and Environmental attitude are included as the householder's individual characteristics. Table 1 displays that the average age of sample householders is 61 years old in 2020 and 62 years old in 2021, the average year of formal education is 7, while nearly 92% of householders are male. According to Liebenehm and Waibel (2014) and Tanaka et al. (2010), far-sighted farmers are more likely to invest a new agricultural technology than near-sighted farmers, since far-sight shows a high degree of patience Duflo et al. (2011). Similarly, Simtowe et al. (2006) and Mao et al. (2019) argued that risk-averse farmers generally hesitate to try new technologies. And Huang et al. (2022) showed that a farmer paying attention to environmental protection is more likely to apply biopesticides. Secondly, we control the family characteristics related to Income, Subsidy, Agricultural labor, and Cooperative member. Family income and subsidy are the vital financial sources of SAS and biopesticide purchase, while the quantity of agricultural labor and becoming cooperative members play an important role in agricultural production decision-making (Igata et al., 2008; Lin et al., 2022). Finally, the farm features are controlled, such as Land, Land fragmentation, and Crop variety. The bigger area of cultivated land or less fragmented farmland the farmers till, the smaller the unit cost and implementation difficulty of SAS operation and biopesticide application (Qiu and Luo, 2021). Moreover, different crop varieties have different demands for SAS and biopesticide (Huang et al., 2003; Huang et al., 2022). Since Qiu and Luo (2021) and Qian et al. (2022) found an inverted U-shaped relationship between farm size and SAS purchase, we also include the square item of Land to capture the heterogeneous effects on SAS purchase.

To explore the impact channels between SAS and biopesticide adoption, we further incorporate two mediator variables into benchmark regression. As listed in Table 1, two possible channels (mediator variables) contain Training (popularization) and Machinery substitution. According to previous studies, purchasing SAS can release the agricultural labor force to wield some new agricultural technologies and machinery to improve agricultural productivity (Baiyegunhi et al., 2019; Picazo-Tadeo and Reig-Martínez, 2006). The decision of adopting biopesticide may be affected by SAS through the above two channels, since biopesticide is viewed as a new capital-intensive agricultural technology.

Table 2 provides the mean differences in controlled characteristics between farmers purchasing SAS and farmers who didn't purchase. As shown in Table 2, farmers who purchased SAS tend to be better educated, more risk-sought, farther-sighted, and more environmentally friendly than farmers who didn't purchase in 2020, while SAS-purchased farmers are better educated and healthier than farmers who didn't purchase in 2021. These findings denote possible self-selection related to the SAS purchase decision. Moreover, households that purchased SAS have more subsidies, larger land sizes, less agricultural labor, and less fragmented land in both years, though the households that had more income and joined cooperatives are more likely to purchase SAS in 2021. Overall, the t-statistics analysis in Table 2 is revelatory about the differences in controlled characteristics and biopesticide adoption between two groups of farmers. However, we cannot draw an inference about the impact of SAS on biopesticide adoption because the results are concluded without controlling other variables and self-selection bias. By contrast, the results drawn from an econometrics analysis are more reliable, which will be introduced in the next section.

5. Results and discussion

Table 3 displays the joint estimation results of farmers' SAS purchase selection model and biopesticides adoption outcome model. Firstly, the likelihood ratio (LR) test in two-stage equation of the ESP model rejects the null hypothesis that ρ_1 is equal to ρ_0 at a significance level of 5%, suggesting that the characteristics of farmers who purchased SAS differ from farmers who didn't. Combining that the ρ_1 is statistically significant, which denotes that SAS does influence the biopesticides adoption decision of purchasers, the application of the ESP model addressing self-selection bias seems to be reasonable. In this context, the results of the two-stage equation are shown separately in the following sub-sections.

5.1. Determinants of SAS purchase

Column 1 of Table 3 shows the influences of covariates on SAS purchase. As regards individual characteristics and family characteristics, education, family income, and cooperative member have a significant positive impact on farmers' SAS purchase decisions. That is, the

Table 2
Mean differences in characteristics by year.

Variables	Year: 2020			Year: 2021		
	Purchasers	*Non-purchasers*	*Diff.*	*Purchasers*	*Non-purchasers*	*Diff.*
Age	61.459	61.276	0.184	62.737	62.509	0.228
	(0.321)	(0.382)	(0.496)	(0.392)	(0.367)	(0.545)
Gender	0.906	0.931	−0.025**	0.928	0.917	0.011
	(0.010)	(0.009)	(0.013)	(0.010)	(0.009)	(0.014)
Education	7.728	6.827	0.901***	7.790	7.053	0.537***
	(0.125)	(0.122)	(0.175)	(0.123)	(0.145)	(0.190)
Health	3.994	3.830	0.164	4.066	3.936	0.130**
	(0.367)	(0.037)	(0.052)	0.036	(0.044)	(0.056)
Risk attitude	1.341	1.277	0.065**	1.310	1.281	0.029
	(0.022)	(0.019)	(0.029)	(0.020)	(0.022)	(0.030)
Time preference	1.762	1.656	0.106***	1.695	1.678	0.017
	(0.026)	(0.025)	(0.036)	(0.023)	(0.028)	(0.036)
Environmental attitude	2.650	2.582	0.068***	2.643	2.630	0.013
	(0.018)	(0.018)	(0.026)	(0.017)	(0.020)	(0.027)
Income (log)	11.436	11.184	0.252***	11.172	11.142	0.030
	(0.055)	(0.041)	(0.068)	(0.053)	(0.048)	(0.072)
Subsidy (log)	6.066	5.222	0.844***	5.935	4.772	1.163***
	(0.070)	(0.106)	(0.125)	(0.093)	(0.107)	(0.148)
Agricultural labor	1.656	1.848	−0.192***	1.671	1.869	−0.198***
	(0.031)	(0.029)	(0.042)	(0.028)	(0.033)	(0.043)
Cooperative member	0.038	0.013	0.025***	0.031	0.008	0.023
	(0.007)	(0.004)	(0.008)	(0.006)	(0.003)	(0.008)
Land (log)	2.033	1.855	0.178***	2.021	1.676	0.345***
	(0.037)	(0.054)	(0.065)	(0.046)	(0.048)	(0.068)
Land fragmentation	0.773	1.525	−0.752***	0.850	1.542	−0.693***
	(0.018)	(0.164)	(0.158)	(0.039)	(0.098)	(0.119)
Biopesticide adoption	0.767	0.088	0.679***	0.814	0.153	0.662***
	(0.014)	(0.010)	(0.018)	(0.016)	(0.012)	(0.020)

Note: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. Standard errors are displayed in parentheses.

Table 3
Determinants of SAS purchase and its impact on Biopesticide adoption.

Variables	Selection	Biopesticide adoption Purchasers	Non-purchasers
	(1)	(2)	(3)
Age	−0.001 (0.004)	−0.009 (0.004)**	0.008 (0.007)
Gender	−0.143 (0.115)	−0.059 (0.138)	−0.057 (0.238)
Education	0.008 (0.003)**	0.024 (0.011)**	0.019 (0.017)
Health	−0.045 (0.034)	−0.033 (0.035)	0.055 (0.054)
Risk attitude	0.052 (0.066)	0.148 (0.069)**	0.082 (0.034)**
Time preference	0.026 (0.049)	0.183 (0.053)***	0.005 (0.084)
Environmental attitude		0.139 (0.069)**	0.298 (0.115)***
Income	0.054 (0.018)***	0.034 (0.035)	0.019 (0.043)
Subsidy	0.011 (0.015)	0.026 (0.013)**	0.012 (0.019)
Agricultural labor	−0.039 (0.043)	0.042 (0.047)	0.162 (0.067)**
Cooperative member	0.089 (0.051)*	0.388 (0.430)	−0.040 (0.316)
Land	0.648 (0.119)***	0.101 (0.044)**	0.656 (0.144)***
Land2	−0.110 (0.018)***	−0.015 (0.023)	−0.066 (0.019)***
Land fragmentation	−0.091 (0.050)*	0.009 (0.053)	−0.033 (0.045)
Crop variety	YES	YES	YES
Region	YES	YES	YES
Year	YES	YES	YES
Constant	1.227 (0.524)**	−0.635 (0.584)	−1.910 (0.843)
Services network (IV)	2.327 (0.144)***		
ρ_1		0.141 (0.068)**	
ρ_0			0.183 (0.111)
Log pseudo-likelihood	−1918.922		
LR test of indep. Eqns. ($\rho_1 = \rho_0$)	$\chi2$ (2) =13.66, Prob > $\chi2$ = 0.016		
Observations	3143		

Note: Standard errors clustered at the household level are shown in parentheses. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. ρ_0 and ρ_1 measure the extent to which SAS influences the biopesticide adoption decision of purchasers and non-purchasers, respectively.

more educated farmers are more likely to realize the comparative advantages of SAS in agricultural production and have more access to its market information, while higher family incomes also help farmers pay for SAS (Luo, 2017; Zhang et al., 2017). Given that smallholders purchasing SAS always bear a relatively higher transaction cost, Ma et al. (2019) and Sun (2017) revealed that the cooperative can integrate members' demand for SAS and bargain with service providers, which confirms the positive effect of joining a cooperative on SAS purchase.

What is striking is that all covariates included in the farm features show a significant influence on farmers' SAS purchases. The estimated results reveal that land size and SAS purchase exist in an inverted U-shaped relationship, which is similar to the findings of Qiu and Luo (2021) and Qian et al. (2022). The reason behind this nonlinear relationship can be that skilled cultivators are more inclined to become service providers themselves with the area of cultivated land growing (Qiu and Luo, 2021). Moreover, as land fragmentation is negatively correlated with service purchase, accelerating the continuous circulation of cultivated land is conducive to large-scale management (Yang et al., 2013).

Additionally, the coefficient of services network (IV) is significant at a significance level of 1%, that is, the peer effects from other villagers can directly influence the farmers' decision to SAS purchase. We also test the validity of this instrumental variable by various methods, though the related results are placed in Appendix C to save space.

5.2. Determinants of biopesticide adoption

The results of the outcome equations listed in columns 2 and 3 (Table 3) display that the drivers of farmers' decisions to adopt biopesticides differ with respect to SAS purchasers and non-purchasers. Compared with the non-significant results of SAS non-purchasers, age, education, time preference, and subsidy show a statistically significant impact on the biopesticides adoption of SAS-purchased households. Stated differently, the younger and more educated the farmers are and the more subsidies they have, the bigger the probability they have to apply biopesticides, while the near-sighted farmers will resist biopesticides for additional costs and uncertainty (Constantine et al., 2020; Mao et al., 2021). By contrast, the significant coefficients of agricultural labor for service non-purchasers suggest that the lack of labor force can hinder the adoption of biopesticides (Nyangau et al., 2022; Yang et al., 2013).

Furthermore, the estimated coefficients of risk attitude, environmental attitude, and land size variables are statistically significant for both service purchasers and non-purchasers, consistent with Huang et al. (2022), Luo et al. (2020), and Tang and Luo (2021). Since the effectiveness of biopesticides perceived by smallholders is sometimes unstable and underrated, the application probability of biopesticides for risk-averse farmers is small. However, both Luo et al. (2020) and Tang and Luo (2021) believe that purchasing insurance could avoid the effect of risk aversion to some extent, and a positive environmental cognition can translate the willingness to buy biopesticides into actual application behavior. Another novel finding is also noteworthy from the perspective of the different roles of land size between service purchasers and non-purchasers. For purchasers, there is a positive linear relationship between land size and biopesticide adoption, while an inverted U-shaped relationship for service non-purchasers. Combined with the findings of Qiu and Luo (2021) and Qian et al. (2022), the probable cause is that farmers are limited by labor and capital in agricultural production, though managing larger farms helps to create economies of scale and apply for subsidies. On the contrary, purchasing SAS can make up for the labor and capital (i.e., plant protection machinery) demands of applying biopesticides.

5.3. Impacts of SAS on biopesticide adoption

Based on the ESP model, the average treatment effect on the treated (ATT) is estimated in Table 4, which reveals the effect of SAS purchase on biopesticides adoption. As shown in Table 4, the ATT of service purchasers is 0.308, denoting that the SAS generates a 30.8% increase in the probability of biopesticides adoption. Moreover, we also show the marginal effect estimated by the Probit model in the lasted column of Table 4. Different from the ATT, the marginal effect of SAS on biopesticides adoption is only 0.162, indicating the underestimated impact without addressing self-selection bias.

In addition, we also conduct two robustness checks by the methods of propensity score matching (PSM) and treatment effect model (TEM) to test the robustness of our main findings. The ATTs estimated by PSM are 0.302 in 2020 and 0.213 in 2021, respectively, while the ATT calculated by TEM is 0.394. Although these estimates are biased for the reasons of ignoring the unobserved factors and heterogeneous features between SAS purchasers and non-purchasers, the positive and significant effects synthetically verify our theoretical hypothesis above. In the interest of space, we report the specific results of two robustness checks in Appendix D.

5.4. Further discussion

This section will further shed some light on the heterogeneous

Table 4
Treatment effects of SAS purchase on Biopesticide adoption.

ESP model			*Probit model*	*PSM*		*TEM*
Mean outcomes		**ATT**	**Marginal effect**	**ATT2020**	**ATT2021**	**ATT**
Purchasers	**Counterfactuals**					
0.37 (0.006)	0.062 (0.001)	0.308*** (0.006)	0.162*** (0.015)	0.302*** (0.064)	0.213*** (0.049)	0.394*** (0.034)

Note: Standard errors are shown in parentheses. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

influence of SAS purchase on different purchasers and explore the potential channels, through which SAS affects the biopesticides adoption decisions of farmers. Put differently, the analyses for the heterogeneous and mediating effects of some key variables are conducted as follows:

5.4.1. Heterogeneous effects of SAS

As previously mentioned, we have reported that the education, cooperative member, and land size variables can affect the farmers' decisions of SAS purchase. Now, we also want to understand whether the effects of SAS on biopesticide adoption vary by these three variables. As shown in the fourth column of Table 5, the treatment effects (ATT) of SAS are all positive and significantly different across subgroups of education, cooperative member, and land size, since the 95% confidence intervals for different subgroups are non-overlapping. Overall, these results denote that the effects of SAS on biopesticide adoption are heterogeneous for different groups of farmers.

Considering education, we found that the ATTs increase with the number of years of schooling. The ATT for farmers with primary school education is 0.258, while the ATTs for farmers with junior high school and high school education are 0.306 and 0.363, respectively. This is likely because the high-educated farmers always have a better ability to process information and adjust production and input plans according to information processing results, therefore, they are more likely to apply a new technology (i.e., biopesticides) introduced by SAS (Lu et al., 2021; Sun et al., 2018). As regards cooperative members, some related studies have shown that joining agricultural cooperatives can provide increase farmers' productivity by providing agricultural production guidance and cheaper agricultural inputs (Candemir et al., 2021; Lin et al., 2022; Sun, 2017). Under the joint impact of cooperatives, the farmers who purchased SAS are more likely to apply biopesticides, which is in line with the results in Table 5.

Based on previous studies, farmers with different land scales may present various demands for SAS (Qiu and Luo, 2021; Qian et al., 2022). Following Lin et al. (2022), farmers were divided into three subgroups according to the size of the land scale in Table 5, and related findings display that the impact of SAS on biopesticide application is illustrated as an inverted U-shaped relationship. Compared with small- and large-scale farmers with ATTs of 0.304 and 0.237, medium-scale farmers benefit more from SAS, where the ATT is 0.401. A possible explanation can be that small farmers grow grain mainly for their own consumption and cannot bear the additional cost of biopesticides, while large-scale farmers may self-apply biopesticides for fewer unit costs and more technology subsidies (Sun et al., 2018).

5.4.2. Potential channels

To verify the potential channels mentioned in the theoretical framework, we further analyze mediating effects proposed by Alan et al. (2018), and display the specific results in Table 6. The percentage mediated denotes the degree the influence is mediated through the potential channels, while a bigger value means the more effective channels (Lin et al., 2022).

Besides the production service, the SAS sometimes provides new crop varieties or techniques to farmers, where accompanied by training or popularization services (Deng et al., 2020; Lu et al., 2021). Since the Chinese government supplies the subsidy of biopesticide to SAS

Table 5
Impact of SAS on Biopesticide (BP) adoption across education, cooperative member, and land size.

Categories	**Mean outcomes**		**ATT**	**[95% Cof. Interval]**
	SAS1-BP1	**SAS0-BP1**		
Education				
Primary school	0.327 (0.011)	0.069 (0.004)	0.258 (0.011)***	[0.236, 0.280]
Junior high school	0.368 (0.009)	0.062 (0.002)	0.306 (0.009)***	[0.288, 0.324]
High school	0.417 (0.011)	0.054 (0.003)	0.363 (0.012)***	[0.340, 0.385]
Cooperative member				
No	0.201 (0.026)	0.091 (0.007)	0.110 (0.027)***	[0.056, 0.164]
Yes	0.374 (0.006)	0.062 (0.001)	0.312 (0.006)***	[0.300, 0.324]
Land size				
Small (0–10 mu)	0.359 (0.007)	0.055 (0.001)	0.304 (0.007)***	[0.291, 0.317]
Medium (10–30 mu)	0.472 (0.018)	0.071 (0.006)	0.401 (0.019)***	[0.364, 0.439]
Large (>30 mu)	0.350 (0.018)	0.114 (0.009)	0.237 (0.020)***	[0.197, 0.276]

Note: Standard errors are shown in parentheses. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$. *SAS1-BP1* and *SAS0-BP1* are the predicted probabilities of biopesticides adoption for SAS purchasers in observed and counterfactual contexts, respectively.

Table 6
Potential mechanisms for the effects of SAS on Biopesticide (BP) adoption.

	Channel 1		**Channel 2**	
	Training or popularization (1)	BP adoption (2)	Machinery substitution (3)	BP adoption (4)
SAS	2.129 (0.150)***	−0.022 (0.016)	3.608 (0.127)***	0.279 (0.212)
Training or popularization		0.013 (0.014)		
Training or popularization × SAS		0.568 (0.229)**		
Machinery substitution				0.058 (0.053)
Machinery substitution × SAS				0.373 (0.098)***
Control variables	YES	YES	YES	YES
Observations	3143			
Controlled direct effects (CDE)	0.376***		0.310***	
Natural direct effects (NDE)	0.228***		0.212***	
Natural indirect effects (NIE)	0.037***		0.075***	
Marginal total effects (MTE)	0.265***		0.287***	
Percentage mediated	86.20%		73.90%	

Note: Percentage mediated = (*NDE/MTE*) × 100%. Standard errors are shown in parentheses. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.

providers, these providers have a strong incentive to recommend biopesticide to farmers in specialized pest control. As stated by Chen et al. (2022) and Lu et al. (2021), the technology popularization provided by SAS can significantly reshape farmers' technology perception of benefit, cost, and risk, and then affect the adoption of new technology. Consistent with Table 6, we find that the impact through this channel accounts for about 86.2%, while the interaction item between training and SAS is positively significant.

On the other hand, some studies have pointed out that biopesticides are sometimes erratic, require multiple applications, and are labor-intensive (Damalas and Koutroubas, 2018; Tang and Luo, 2021). However, if farmers purchase the SAS with mechanical spraying services, they may be more likely to apply the biopesticides for the reason of machinery substitution. Stated differently, the SAS can stimulate the application of biopesticides by reducing labor constraints (Yang et al., 2013). The last two columns of Table 6 show that the SAS accelerates machinery substitution with a significant coefficient (3.608), combined with the significant coefficient of the interaction term, the machinery substitution finally displays the mediating effects of 73.9%.

6. Conclusions and policy implications

Global climate change is aggravating the occurrence of pests and diseases, biopesticide application, a component of climate-smart agricultural practices, is viewed as an environmentally-friendly substitute for chemical pesticides, especially when pesticide residue is emerging as a worldwide issue with a great threat to the ecological environment, human health, and food security. Due to the additional cost attached to externalities and information insufficiency, the biopesticide application willingness of smallholders is depressed at the present stage. Given that the specialized agricultural service (SAS) has been viewed as a bridge effectively connecting smallholders with major factor markets in China, a theoretical framework of whether and how SAS for specialized pest control affects farmers' biopesticide application practices was built in this study. We then used the survey data from Jiangsu province of China and applied the endogenous switching probit (ESP) model to further verify the impact of SAS on farmers' biopesticide adoption behavior and its potential channels. The robustness checks using alternative estimation strategies finally confirmed the ESP results.

Our study reveals that the SAS purchase can significantly increase the probability of biopesticide adoption by 30.8%. Without considering the self-selection bias, this probability will drop to 16.2%. The potential influence channels through which the SAS promotes the biopesticide application are technology popularization (training) and machinery substitution resulting from SAS. Moreover, the ESP results suggest that the farmers with more educated, higher income, an identity of cooperative member, and less fragmented land are more likely to purchase SAS, while an inverted U-shaped relationship between land size and SAS purchase is found. Concerning biopesticide adoption, the risk attitude, environmental attitude, and land size all present statistically significant effects on both the SAS purchasers and non-purchasers. Not only that, our results also denote that the effects of SAS on biopesticide adoption are heterogeneous, and vary with education level, cooperative member, and land size. Put differently, these effects are greater if a farmer is more educated or a cooperative member, while they increase first and then decrease with the expansion of land scale.

In addition to providing services of expertise and farm machinery, our empirical results reveal that SAS can significantly promote the adoption of CSAPs such as biopesticides. Hence, our study not only provides a new idea for the promotion of biopesticides, but also further confirms the crucial role of SAS in effectively connecting smallholders with agricultural modernization production. Some important implications for policymakers are vigorously supporting the development of SAS, while viewing it as a complement to the public extension department in biopesticide promotion activities, and strengthening its role in technical training (popularization) and the supply of agricultural machinery. Besides the above mentioned, the policy instruments, such as subsidy for biopesticide and policy-based insurance, should be tilted towards both appropriate land & service management subjects and cooperative organization, when the land size and cooperatives contribute a lot to SAS development and biopesticide promotion.

What is noteworthy is that our findings are highly relevant to other developing countries, such as Africa and Southeast Asia, where the agricultural sector is mainly composed of smallholders and the markets of SAS are emerging. This empirical study is expected to provide a basis for further research about the influences of SAS on biopesticide promotion in developing areas. Furthermore, the attempt in this line may accelerate the growth of biopesticide global market share, which contributes to climate change adaptation, agricultural sustainable development, and food safety. However, due to some insuperable problems in the survey, this study did not subdivide the specific types and usage amount of biopesticides, and only the average effect of SAS on the application of biopesticides could be estimated. This deficiency needs to be eliminated by future research.

Credit authorship contribution statement

Hongyun Han: Conceptualization, Writing revision and editing;
Kai Zou: Idea, Methodology, Data processing, Writing-original draft and Writing revision and editing;
Zhen Yuan: Data processing and editing.

Declaration of competing interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2024.107430.

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