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The application of organic fertilizers and farmers' income increase

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Abstract

The extension of organic fertilizers helps improve soil quality and reduces non-point source pollution caused by excessive use of fertilizers, however, whether the application of organic fertilizers (OFA) contributes to an increase in farmers' income is a matter of debate. This paper discussed how the application of soil-testing formulas and outsourcing services that some or all links of agricultural production to professional organizations moderate the income-increasing effect of OFA, and Multinomial Endogenous Switching Regression Model (MESR) is selected to do the empirical test. The results indicate that OFA with soil-testing formula and OFA with outsourcing service can effectively increase farmers' income, in specific, OFA with soil-testing formula increases the net monetary income of wheat growing on per hectare (ha) of land by 2150 Renminbi (RMB), and OFA with outsourcing service increases the net monetary income of wheat growing on per ha of land by 3950 RMB, however, OFA has no effectiveness on increasing farmers' income if neither soil-testing formulas nor outsourcing services is available. The influence mechanism of OFA to improve farmers' income is to increase crop yield, but OFA has no effectiveness on increasing the price of products. A systematic extension services including the extension of organic fertilizers, soil testing formulas and outsourcing services should be formed in the future.

Introduction

Long-term Overuse of fertilizers has led to soil quality degradation, non-point-source pollution, and high production costs (Uhunamure et al., 2021). Despite this, the amount of chemical fertilizer used per hectare of planting area in 2020 was 313.5 kg/ha, significantly exceeding the internationally recognized upper limit of chemical fertilizer input of 225 kg/ha (Li, 2019). To address this, the Chinese government encourages the use of organic fertilizers as an alternative to reduce the excessive use of chemical fertilizers (Zhan et al., 2021). The adoption of organic fertilizers is mainly driven by market forces, and farmers are more likely to use them if organic fertilizer application (OFA) increases their income (Gao et al., 2022). Numerous agronomic experiments have demonstrated that OFA positively impacts crop yield and product quality, enhancing the competitiveness and market price of these products (Choudhary et al., 2022; Du et al., 2022; Jiang et al., 2022*a*; Tao et al., 2022).

In contrast to the consistent results obtained from agricultural experiments, social science studies have reached varied conclusions. Some empirical studies have found a positive effect of OFA on farmers' income (Chen, Fu, and Liu, 2022), while others have found that OFA does not significantly improve farmers' income (Su, Zhou, and Zhou, 2022). Some technical considerations are necessary to ensure that OFA positively impacts farmers' income. First, since organic fertilizers have a lower nutrient content and release nutrients more slowly than chemical fertilizers (Fertahi et al., 2021), it is essential to use both organic and chemical fertilizers in precise proportions to enhance crop yield and quality (Hauck and Bremner, 1976). Second, artificial fertilization methods cannot deliver fertilizers to the deep soil, reducing fertilizer utilization efficiency (Wang et al., 2021). However, farmers face various social and economic constraints which may reduce the effectiveness of OFA on increasing farmers' income. Firstly, since most farmers in China have not systematically studied professional agricultural knowledge, they mainly rely on ancestral teachings and personal experience to decide how much fertilizer to use, which is often imprecise (Zheng et al., 2023). Secondly, diseconomies of scale prevent farmers from buying machinery, and mechanical fertilization is not widespread among them (Baruah, Mohanty, and Rola, 2022). Thirdly, farmers face information asymmetry and often purchase inferior fertilizers, while the scattered layout of fertilizer retail stores makes it difficult for the government to regulate the quality of fertilizers (Amfo and Baba Ali, 2021). Finally, many smallholders have limited access to technical support because the government tends to be more inclined to provide technical support for large-scale farmers (Qing et al., 2023). These constraints prevent OFA from achieving the expected technical performance. However, this issue can be alleviated by extending soil-testing formulas and outsourcing services. Soil-testing formulas, a type of precision fertilization technique, are widely promoted in rural China (Dong et al., 2023). By measuring the nutrient content in the soil, the precise amount of fertilizer needed is determined, avoiding the excessive or insufficient fertilizer inputs typically caused by farmers' decisions. Outsourcing services involve delegating some or all aspects of agricultural production to professional organizations such as cooperatives or agricultural machinery stations, which can mitigate the limitations of individual farmers through the division of labor (Chen, Zhong, and Lu 2023). Therefore, theoretically, the effectiveness of OFA may be enhanced if organic fertilizers are applied using soil-testing formulas or outsourcing services.

Previous studies have overlooked the potential impact of extending soil-testing formulas and outsourcing services on moderating the effectiveness of OFA on farmers' income. This article's innovation mainly revolves around two aspects. Firstly, it analyzes how soil-testing formulas and outsourcing services enhance the effectiveness of OFA in augmenting farmers' income, utilizing survey data for empirical testing. Secondly, it examines the mechanisms by which OFA increases farmers' income, testing both its effects on yield and price.

Theoretical analysis

The influence mechanism by which soil-testing formulas and outsourcing services enhance the effectiveness of OFA in increasing farmers' income is illustrated in Figure 1.

The effectiveness of OFA improved by the soil-testing formula

As a form of precise fertilization technology, soil-testing formulas, vigorously promoted by the Chinese government, help farmers enhance the accuracy of OFA (Sun and Li, 2021; Zheng et al., 2023). Based on soil test field experiments, these formulas can be made by local fertilizer stations or cooperatives, utilizing soil nutrient content measurements to precisely replenish missing nutrients in the soil (Zhang et al., 2021). Consequently, the application of soil-testing formulas not only determines precise fertilizer inputs, leading to improved crop yields, but also reduces fertilizer residue, thereby enhancing crop quality (Li et al., 2022*b*). Theoretically, the economic benefits of OFA can be realized through the use of soil-testing formulas, and this article proposes the following hypothesis:

H1: The application of soil-testing formulas improves the effectiveness of OFA in increasing farmers' income.

The effectiveness of OFA improved by outsourcing services

Outsourcing services help alleviate the inefficiencies of OFA resulting from farmers' limitations in accessing information, machinery, and technical support. Firstly, professional organizations have stronger market negotiation skills than farmers, enabling them to purchase fertilizers at lower prices (Rutsaert et al., 2021). In addition, these organizations can mitigate the information asymmetry regarding fertilizer quality that often hinders farmers, thus ensuring the acquisition of high-quality fertilizers (Li et al., 2021). Secondly, professional organizations employ mechanized fertilization, facilitating the delivery of fertilizers to deep soil layers and thus enhancing operational efficiency (Chen, Zhong, and Lu 2023). Thirdly, professional organizations have better access to government-provided technical support compared to individual farmers (Mattila et al., 2021). In theory, the economic effects of OFA can be enhanced through the implementation of outsourcing services, and this article proposes the following hypothesis:

H2: The implementation of outsourcing services improves the effectiveness of OFA in increasing farmers' income.

Data and method

Empirical model

The dependent variable in this paper is farmers' income, measured by the variable 'net income of wheat (*Triticum aestivum* L.) per hectare of land' (*NIW*). This variable is calculated by subtracting total costs, including the cost of seedlings, fertilizers, pesticides, irrigation, machinery, labor, and land rent, from total revenue. The key independent variables represent farmers' behaviors regarding OFA, encompassing several choices: applying no organic fertilizers, OFA with soil-testing formula, OFA without soil-testing formula, OFA with outsourcing service, and OFA without outsourcing service, with farmers applying no organic fertilizers considered the control group. The two key independent variables are 'whether organic fertilizer is applied with soil-testing formula (*OSF*)' and 'whether organic fertilizer is applied with outsourcing service (*OUS*)'. Farmers' selections of OFA are not random behaviors. They are influenced by various factors, such as technical training, which may also impact farmers' income, potentially leading to self-selection bias (Ma and Abdulai, 2016). Reliable estimates of OFA's effect on farmers' income cannot be obtained without addressing self-selection bias (Vigani et al., 2019). The Propensity Score Matching Model (PSM) cannot correct for self-selection bias resulting from unobservable factors (Abdulai,

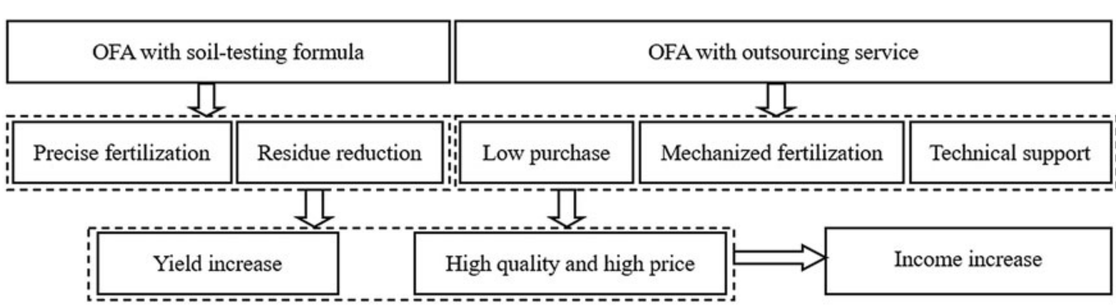

Figure 1. The influence mechanism that soil-testing formula and outsourcing service drive the effectiveness of OFA.

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2016), and the Difference-in-Difference Model (DID) cannot be applied to cross-sectional data (Pan, Lu, and Kong, 2022). Therefore, the Multinomial Endogenous Switching Regression Model (MESR) is chosen to address the self-selection bias issue (Deb and Trivedi, 2006), and the IV-2sls method is selected to test the robustness of the results.

The MESR comprises three stages. In the first stage, a Multinomial Logit Model (Mlogit) is used to estimate the probability of farmers choosing various behaviors related to OFA. This article assumes that there are k selections in total.

$$S = \begin{cases} 1 \quad \textit{if } U_{i1}^{*} < \max\limits_{n \neq k}(U_{\text{in}}^{*}) \\ \cdots \\ k \text{ if } U_{ik}^{*} > \max\limits_{n \neq k}(U_{\text{in}}^{*}) \end{cases} \qquad n \neq k \tag{1}$$

S represents all the k selections made by famers. '$S = 1$' represents the absence of OFA, serving as the control group, while '$S =$ 2, 3■■■k' represents the other selections, including OFA with soil-testing formula, OFA without soil-testing formula, OFA with outsourcing service, and OFA without outsourcing service. U_{ik}^{*} represents the utility attained by farmers from the kth selection. The selection equation can be represented by Equation (2).

$$U_{ik}^{*} = \beta_k X_{ik} + \varepsilon_{ik} \tag{2}$$

X_{ik} represents the observable factors that may influence farmers' selection, including the characteristics of the household head and family (Lee, 2005). Household head characteristics that may impact OFA include the 'age of the household head (*AGE*)' (Oyetunde-Usman, Olagunju, and Ogunpaimo, 2021), 'gender of the household head (*GEN*)' (Makate and Mutenje, 2021), 'years of education of the household head (*EDU*)' (Ojo and Baiyegunhi, 2021), 'risk preference of the household head (*RPH*)' (Qiao and Huang, 2021), 'whether the household head has received technical training (*HRT*)' (Maertens, Michelson, and Nourani, 2021), 'whether the household head is a village cadre (*HVC*)' (Li et al., 2022*a*), and 'whether the household head is a member of a cooperative (*HMC*)' (Zhang et al., 2023). Family characteristics include 'per capita household income (*PHI*)' (Setsoafia, Ma, and Renwick, 2022), 'number of household labor force (*NHL*)' (Qian et al., 2022), 'size of farm (*SOF*)' (Hu et al., 2022), and 'proportion of non-farm income to total household income (*PNT*)' (Wesenbeeck et al., 2021). Additionally, the instrumental variable 'distance between farmers and the nearest store selling organic fertilizers (*WOV*)' is included in Equation (2). This variable reduces transaction costs associated with accessing organic fertilizer by allowing farmers to purchase it from nearby stores (Jiang et al., 2022*b*), which also provide farmers with information related to OFA, aiding in the rational use of organic fertilizers (Li et al., 2022*a*). Therefore, '*WOV*' and OFA are highly correlated, but '*WOV*' does not directly impact farmers' income, making it a suitable instrumental variable for this article.

β_k is the estimated coefficient of X_{ik}. ε_{ik} represents unobservable variables assumed to follow an independent and identical Gumbel distribution. Thus, the probability of the kth selection by the farmer, characterized by X_i can be calculated by Equation (3) (McFadden, 1974).

$$P_{ik} = Pr\left(U_{ik}^{*} > \max_{n \neq k}(U_{\text{in}}^{*}|X_i)\right) = \frac{\exp(X_i\beta_k)}{\sum_{n=1}^{k}\exp(X_i\beta_n)} \tag{3}$$

In the second stage, an income determination equation is constructed to estimate the effects of various OFA selections on farmers' income. In this article, farmers have k different selections, with each corresponding to its own income determination equation.

$$\begin{aligned} &S = 1{:}\ NIW_{i1} = \alpha_1 Z_{i1} + \mu_{i1} \\ &\cdots \end{aligned} \tag{4}$$

$$S = K{:}NIW_{ik} = \alpha_k Z_{ik} + \mu_{ik} \tag{5}$$

$S = 1$ represents the condition where farmers do not apply organic fertilizers, considered the control group. NIW_{i1} represents the income of those farmers who do not use organic fertilizer, while NIW_{ik} represents the income of farmers employing the kth selection of OFA methods. Z represents all factors that may impact farmers' income. The variable μ_{ik} satisfies the equation $E(\mu_{ik}|X, Z) = 0$ and $\text{var}(\mu_{ik}|X, Z) = \sigma_k^2$. If OLS is used to estimate equation (5), biased results may be obtained (Teklewold et al., 2013). Therefore, a correction item is added to equation (5) to replace the selection of OFA (Kumar et al., 2019). This article assumes that μ_{ik} is highly correlated with farmers' selections, leading to the modification of Equations (4) and (5) into Equations (6) and (7).

$$\begin{aligned} &S = 1\ NIW_{i1} = \alpha_1 Z_{i1} + \sigma_1\hat{\lambda}_{i1} + \omega_{i1} \\ &\cdots \end{aligned} \tag{6}$$

$$S = k\ NIW_{ik} = \alpha_k Z_{ik} + \sigma_k\hat{\lambda}_{ik} + \omega_{ik} \tag{7}$$

σ_k represents the covariance of ε_{ik} and μ_{ik}, and unbiased estimates of σ_k can be obtained. ω_{ik} represents the error term with an expected value of zero. $\hat{\lambda}_{ik}$ represents the Inverse Mills Ratio, which is calculated based on the probability of the kth selection by farmers.

$$\hat{\lambda}_{ik} = \sum_{n \neq k}^{k} \rho_k \left[\frac{\hat{\rho}_{ni}\ln(\hat{\rho}_{ni})}{1 - \hat{\rho}_{ni}} + \ln(\hat{\rho}_{ik})\right] \tag{8}$$

ρ represents the correlation coefficient of ε_{ik} and μ_{ik}. The standard error in Equation (6) can be obtained using the bootstrap method to account for the heteroscedasticity that arises when generating $\hat{\lambda}_{ik}$.

In the third stage, the average treatment effects (ATT) of different OFA methods on farmers' income are estimated by comparing their income under factual and counterfactual scenarios.

The expected income value of farmers who made the kth selection can be calculated using Equation (9).

$$E(NIW_{ik}|U = k, Z_{ik}, \hat{\lambda}_{ik}) = \alpha_k Z_{ik} + \sigma_k\hat{\lambda}_{ik} \tag{9}$$

The expected income value of farmers making the kth selection in the counterfactual state can be calculated using Equation (10).

$$E(NIW_{i1}|U = k, Z_{ik}, \hat{\lambda}_{ik}) = \alpha_1 Z_{ik} + \sigma_1\hat{\lambda}_{ik} \tag{10}$$

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The unbiased estimation results of the ATT can be calculated using Equation (11).

$$\begin{aligned} \text{ATT} &= E(NIW_{ik}|U = k, Z_{ik}, \hat{\lambda}_{ik}) \\ &\quad - E(NIW_{i1}|U = k, Z_{ik}, \hat{\lambda}_{ik}) \\ &= Z_{ik}(\alpha_k - \alpha_1) + \hat{\lambda}_{ik}(\sigma_k - \sigma_1) \end{aligned} \tag{11}$$

When examining the influencing mechanism, the variable 'yield of wheat on per ha of land (*YWH*)' is chosen to assess the impact of '*OSF*' and '*OUS*' on crop yield, while the variable 'proportion of wheat price exceeding the village's average wheat price (*PWA*)' is selected to evaluate the effects of '*OSF*' and '*OUS*' on wheat price. We do not use wheat price as a dependent variable due to its significant regional variation (Langridge and Reynolds, 2021).

Study site

The study was conducted in Anhui Province, China, in 2021. Anhui is one of the most important grain-producing provinces in eastern China, encompassing the production of cereals, legumes, and tuber within its grain production sector. Data from the China Statistical Yearbook indicates that Anhui Province's grain production in 2022 reached 411,001 million kg, ranking fourth among all provinces in China. Firstly, 18 counties with the highest grain output in Anhui Province in 2022 were selected as our sample sources. Second, these 18 counties were ranked based on their grain output in 2022. From this ranking, 6 counties were chosen as sample counties in this paper using equidistant sampling method. Among these 6 sample counties, 3 are situated north of the Huai River, comprising Funan County, Lixin County, and Yongqiao County, where wheat and maize are the primary crops. The remaining 3 counties are located south of the Huai River and north of the Long River, namely Feixi County, Mingguang County, and Dingyuan County, where rice (Oryza sativa L.) and wheat are the predominant crops. Figure 2 depicts the geographic locations of the sample counties.

Data

Data were collected through a survey of grain-growing households located in the county study sites in 2021. The survey involved face-to-face questionnaires with household heads. A multi-stage clustered random sampling strategy was employed to derive the household sample. Specifically, within each sample county, high-, middle-, and low-income towns were identified based on the index of per capita disposable income, with one town of each income level selected. Subsequently, all villages within each selected town were categorized into high- and low-income villages, from which one village of each type was chosen. Within each village, rural households were further divided into large-scale farmers managing at least 3.33 hectares of land and smallholders managing less than 3.33 ha (Note. Anhui province belongs to the region of two-harvest-a-year. According to the standard set by Ministry of Agriculture and Rural Affairs of the People's Republic of China, farmers who operate on at least 3.33ha of farmland in the region of two-harvest-a-year are classed as large-scale farmers (Guo, Zhong, and Ji, 2019)). 10 large-scale farmers and 10 smallholders were then selected from each village. This sampling strategy resulted in 720 households being selected for the survey (36 villages in 18 towns across 6 counties). Among them, 104 surveyed households did not grow wheat and were therefore excluded from the total sample, leaving 616 effective samples.

Results

Results of descriptive statistics

The results of the descriptive statistics for all the variables are presented in Table 1. The net income and yield of wheat cultivation vary significantly among farmers. However, the price of wheat

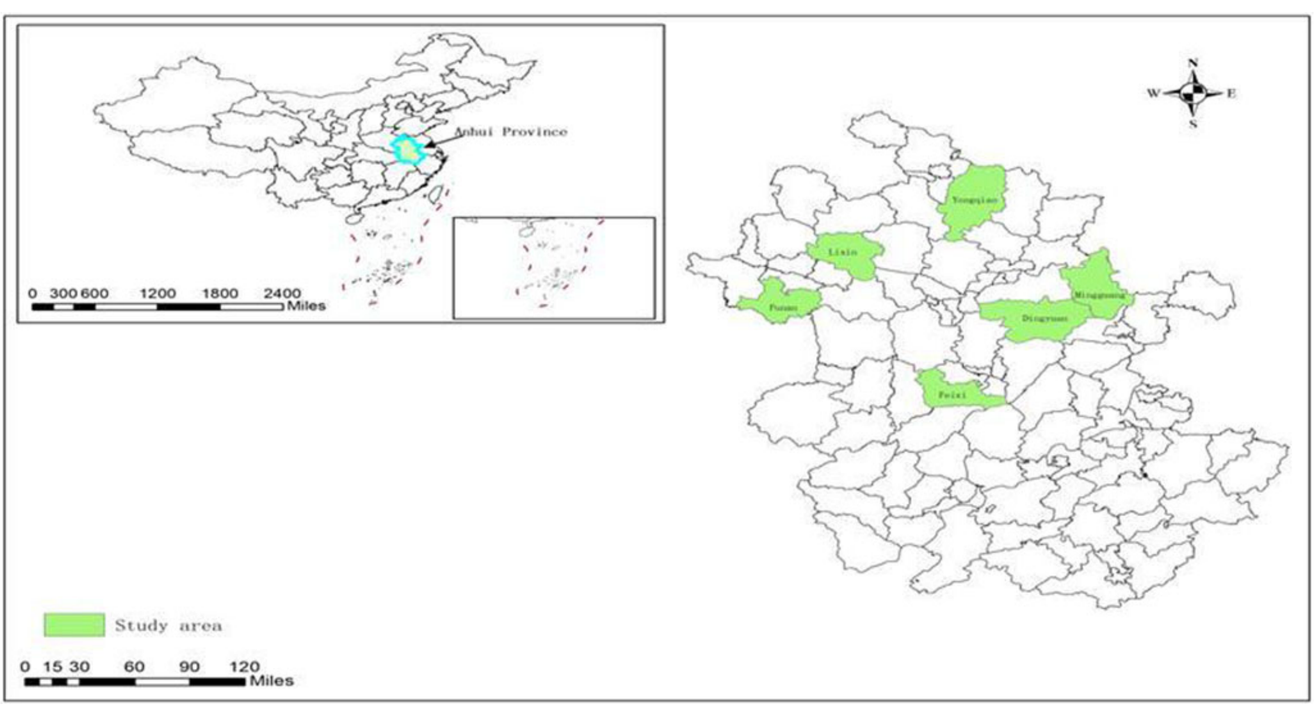

Figure 2. Location of Anhui Province and the province's 6 grain-producing counties that are the study sites.

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Table 1. Descriptive statistics of the variables

Variables	Instructions of variables	Mean	Standard deviation	Max	Min
Dependent variables					
Net income of wheat growing on per ha of land (*NIW*)	The revenue of wheat growing minus the cost, and the unit is 10000RMB/ha	0.58	0.34	1.91	0.01
Wheat yield on per ha of land (*YWH*)	The unit is 1000 kg/ha	6.04	1.45	9	0.62
The proportion of wheat price above the average wheat price of the village (*PWA*)	The unit is %	0.38	4.11	9.95	−9.33
Independent variables					
Whether organic fertilizer is applied with soil-testing formula (*OSF*)	0 = Not applying organic fertilizers, 1 = OFA without soil-testing formula, 2 = OFA with soil-testing formula	0.64	0.82	2	0
Whether organic fertilizer is applied with outsourcing service (*OUS*)	0 = Not applying organic fertilizers, 1 = OFA without outsourcing service, 2 = OFA with outsourcing service	0.56	0.73	2	0
Age of the household head (*AGE*)	2020 minus the birth year	50.24	8.89	76	27
Gender of the household head (*GEN*)	0 = female, 1 = male	0.9	0.3	1	0
Years of education of the household head (*EDU*)	Computation from primary school	8.42	2.95	16	0
Risk preference of the household head (*RPH*)	0 = risk aversion, 1 = risk neutrality, 2 = risk preference	1.09	0.67	2	0
Whether the household head has received technical training (*HRT*)	0 = No, 1 = Yes	0.68	0.47	1	0
Whether the household head is a village cadre (*HVC*)	0 = No, 1 = Yes	0.28	0.45	1	0
Whether the household head is a member of cooperative (*HMC*)	0 = No, 1 = Yes	0.47	0.5	1	0
Per capital household income (*PHI*)	The unit is 10000RMB	3.61	5.48	70	0.1
The number of household labor force (*NHL*)		2.99	1.33	10	0
The size of farm (SOF)	The unit is ha	8.31	21.75	366.17	0.07
the proportion of non-farm income to total household income (*PNT*)	The unit is %	47.1	38.69	100	0
The distance between farmers and the nearest store selling organic fertilizers (*WOV*)	The instrumental variable, and the unit is km	0.6	0.49	1	0

fluctuates within a small range, with the selling price typically within 10% above or below the average price in their villages. Among the farmers, 257 (41.72%) use organic fertilizers. Of these, 135 (52.53%) combine organic fertilizers with soil-testing formulas, and 86 farmers (33.46%) use organic fertilizers with outsourcing services. This indicates that organic fertilizers are not yet widely used in rural China, and the combined application of organic fertilizers with soil-testing formulas and outsourcing services needs further promotion.

Validation of the instrumental variable

The variable 'the distance between farmers and the nearest store selling organic fertilizers (*WOV*)' is selected as the instrumental variable. We test its validity, and the results are presented in Table 2. The outcome of the KPrkLM test rejects the null hypothesis at the 1% significance level, indicating that *WOV* is correlated with both *OSF* and *OUS*. Additionally, the value of CDWF exceeds the Stock Yogo weak ID test's critical value of 16.38 at the 10% level, indicating that *WOV* is not a weak instrumental variable.

The results of T-test

The T-test was conducted to identify differences between farmers who apply organic fertilizers and those who do not. The results are presented in Table 3. It is evident that the differences in

Table 2. The validation of instrumental variable

Tests	*OSF*	*OUS*
Kleibergen-Paap rk LM (KPrkLM)	174.815***	113.447***
Cragg-Donald Wald F (CDWF)	252.283	143.170

Note. *, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

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Table 3. The results of *T*-test

Variables	A	B	C	B-A	C-A	D	E	D-A	E-A
AGE	52.68	48.01	49.70	−4.67***	−2.98***	47.92	50.85	−4.76***	−1.83*
GEN	0.90	0.90	0.91	0.00	0.01	0.89	0.96	−0.01	0.06*
EDU	7.65	8.81	8.96	1.16***	1.31***	8.94	8.74	1.29***	1.09***
RPH	0.62	1.34	1.40	0.72***	0.78***	1.33	1.46	0.71***	0.84***
HRT	0.50	0.65	0.95	0.15***	0.45***	0.73	0.91	0.23***	0.41***
HVC	0.30	0.28	0.26	−0.02	−0.04	0.28	0.25	−0.02	−0.05
HMC	0.43	0.46	0.54	0.03	0.11**	0.47	0.55	0.04	0.12**
PHI	2.36	4.49	4.19	2.13***	1.83***	4.18	4.74	1.82***	2.38***
NHL	3.17	2.88	2.88	−0.29**	−0.29**	2.92	2.79	−0.25**	−0.38**
SOF	2.62	11.41	12.06	8.79***	9.44***	10.63	14.27	8.01***	11.65***
PNT	46.47	50.90	43.40	4.43	−3.07	49.95	41.60	3.48	−4.87
WOV	0.50	0.38	0.38	−0.12**	−0.12**	0.39	0.34	−0.11**	−0.16***

A, Not applying organic fertilizers; B, OFA without soil-testing formula; C, OFA with soil-testing formula; D, OFA without outsourcing service; E, OFA with outsourcing service.
*, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

AGE, *EDU*, *RPH*, *HRT*, *HMC*, *PHI*, *NHL*, *SOF*, and *WOV* between farmers not applying organic fertilizers and those applying organic fertilizers with soil-testing formulas are statistically significant at the 5% level. Similarly, the differences in *EDU*, *RPH*, *HRT*, *HMC*, *PHI*, *NHL*, *SOF*, and *WOV* between farmers not using organic fertilizers and those using organic fertilizers with outsourcing services are statistically significant at the 5% level. These results indicate that the behavior of farmers regarding OFA is not random and may be influenced by numerous factors. Therefore, MESR is suitable for solving the estimation bias caused by the non-randomness of this behavior.

The results of Mlogit

Mlogit is chosen in the first stage of MESR to estimate the probability of OFA, and the results are reported in Table 4. The results of marginal effects indicate that most variables significantly influence farmers' OFA behavior. These results demonstrate that OFA is not a random behavior among farmers, justifying the use of MESR over OLS. As farmers age, the probability of OFA without soil-testing formula and OFA without outsourcing service decreases, while the probability of OFA with soil-testing formula and OFA with outsourcing service increases. This indicates that older farmers accumulate more planting experience than younger farmers, which helps them enhance technology application (Thar et al., 2021). The probability of OFA with outsourcing service is higher in males than in females, indicating that men are more adventurous than women in terms of technology application (Qing et al., 2023). Risk preference increases the likelihood of OFA, and receiving technical training encourages farmers to use organic fertilizers with soil-testing formulas, consistent with previous studies (Ambali, Areal, and Georgantzis, 2021). The probability of OFA with the soil-testing formula is higher among village cadres than among ordinary farmers. This is because village cadres have more positive attitudes toward technology application, as they need to maintain their prestige in rural society by leading in technology application (Peng and Yang, 2021). Being a member of a cooperative increases the probability of OFA with outsourcing services but decreases the probability of OFA without outsourcing services. This is because cooperatives usually provide outsourcing services to farmers (Xie, Luo, and Zhong, 2021). Conversely, an abundant household labor force reduces the likelihood of OFA with outsourcing services, as their own labor force is enough to support agricultural production, thereby decreasing the demand for outsourcing services (Brown et al., 2021). An increase in farm size increases the probability of OFA. This is because land consolidation through transfer reduces land fragmentation, thereby enhancing the economies of scale for OFA (Helfand and Taylor, 2021). The instrumental variable WOV has a negative impact on farmers' OFA behavior, aligning with expectations and confirming the validity of the instrumental variable.

The results of ATT

The results of the ATT estimated by MESR are presented in Table 5. They indicate that neither OFA without a soil-testing formula nor OFA without an outsourcing service significantly increases the net income of wheat cultivation per hectare. However, OFA with a soil-testing formula increases the net income of wheat cultivation per hectare by 2150 RMB, and OFA with an outsourcing service increases it by 3950 RMB. Both results are statistically significant at the 1% level. These results confirm H1 and H2, suggesting that the effectiveness of OFA in increasing income can be enhanced by the application of a soil-testing formula or an outsourcing service.

The Kernel density (K-density) of farmers not applying organic fertilizers, applying organic fertilizers without a soil-testing formula, and applying organic fertilizers with a soil-testing formula are depicted in Figure 3. When compared with farmers not using organic fertilizers, the shift of Kdensity for farmers using organic fertilizers without a soil-testing formula to the right is not noticeable. However, there is a clear rightward shift in the Kdensity for farmers applying organic fertilizers with soil-testing formulas. These results indicate that OFA without a soil-testing formula has no significant effect on the net income of wheat cultivation, whereas OFA with a soil-testing formula has a significantly positive impact on the net income of wheat cultivation.

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Table 4. The results of Mlogit

	OFA without soil-testing formula		OFA with soil-testing formula		OFA without outsourcing service		OFA with outsourcing service	
Variables	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
AGE	−0.027* (0.016)	−0.006*** (0.002)	0.016 (0.018)	0.005** (0.002)	−0.031* (0.016)	−0.007*** (0.002)	0.027 (0.023)	0.004*** (0.001)
GEN	0.455 (0.392)	0.026 (0.056)	0.586 (0.464)	0.038 (0.051)	0.425 (0.388)	−0.029 (0.057)	1.525** (0.677)	0.098** (0.048)
EDU	0.078 (0.050)	0.003 (0.007)	0.121** (0.056)	0.009 (0.006)	0.089* (0.050)	0.010 (0.007)	0.078 (0.069)	0.001 (0.005)
RPH	2.266*** (0.258)	0.183*** (0.027)	2.354*** (0.278)	0.113*** (0.023)	2.291*** (0.250)	0.188*** (0.025)	2.931*** (0.347)	0.091*** (0.019)
HRT	0.362 (0.268)	−0.187 (0.142)	2.784*** (0.429)	0.342*** (0.047)	0.766 (0.269)	−0.011 (0.040)	2.102*** (0.468)	0.123*** (0.033)
HVC	−0.417 (0.283)	−0.009 (0.039)	0.702** (0.320)	0.057* (0.034)	−0.534* (0.280)	−0.046 (0.039)	−0.655 (0.410)	−0.019 (0.028)
HMC	−0.379 (0.258)	−0.052 (0.036)	−0.158 (0.291)	0.013 (0.031)	−0.347 (0.259)	−0.075** (0.035)	0.268 (0.359)	0.045* (0.024)
PHI	0.037 (0.041)	0.006 (0.004)	0.010 (0.042)	−0.002 (0.003)	0.061 (0.045)	0.005 (0.005)	0.081* (0.049)	0.003 (0.002)
NHL	−0.094 (0.098)	−0.006 (0.014)	−0.113 (0.105)	−0.007 (0.011)	−0.075 (0.098)	0.005 (0.013)	−0.271** (0.131)	−0.017** (0.009)
SOF	0.106*** (0.021)	0.009*** (0.002)	0.100*** (0.022)	0.004*** (0.001)	0.114*** (0.022)	0.011*** (0.002)	0.119*** (0.023)	0.002*** (0.001)
PNT	0.006* (0.003)	0.001* (0.000)	0.003 (0.004)	−0.000 (0.000)	0.006* (0.003)	0.001** (0.000)	0.002 (0.005)	−0.000 (0.000)
WOV	−0.678*** (0.226)		−0.857*** (0.321)		−1.447*** (0.281)		−4.828*** (0.630)	
Constant term	−2.907** (1.131)		−9.180*** (1.385)		−3.422*** (1.132)		−14.132*** (1.863)	
Wald	217.090***				228.190***			
Log likelihood	−449.872				−371.369			
Observations	616				616			
Pseudo R^2	0.332				0.421			

Note. Standard errors are reported in parentheses, and *, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

Table 5. The results of ATT

Variable	Treat	Treatment group		
		Real value	Counterfactual value	ATT
NIW	OFA without soil-testing formula	0.518 (0.006)	0.492 (0.005)	0.026 (0.018)
	OFA with soil-testing formula	0.787 (0.008)	0.572 (0.005)	0.215*** (0.010)
	OFA without outsourcing service	0.537 (0.004)	0.535 (0.006)	0.002 (0.006)
	OFA with outsourcing service	0.887 (0.017)	0.492 (0.008)	0.395*** (0.020)

Note. Standard errors are reported in parentheses, and *, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

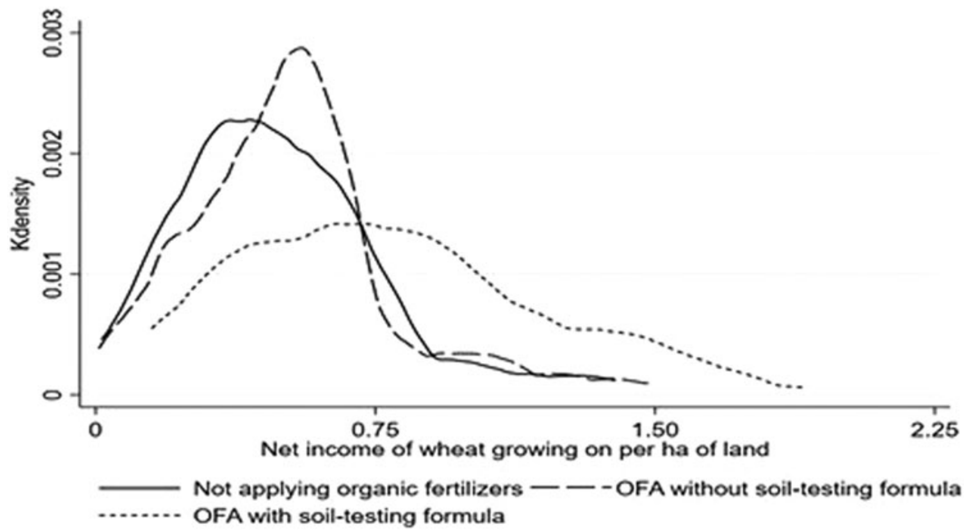

Figure 3. The Kdensity of OFA with soil-testing formula.

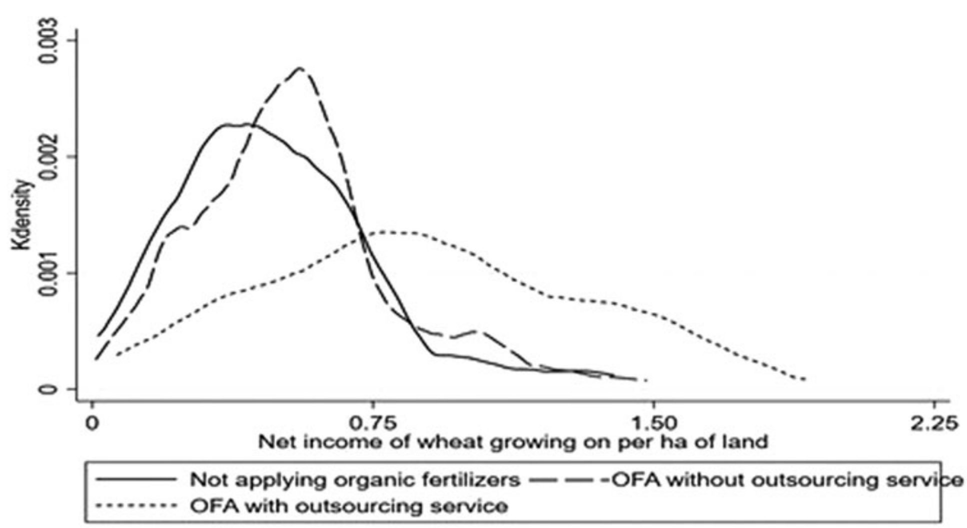

Figure 4. The Kdensity of OFA with outsourcing service.

The K-density of farmers not applying organic fertilizers, applying organic fertilizers without outsourcing service, and applying organic fertilizers with outsourcing service are presented in Figure 4. When compared with farmers not applying organic fertilizers, the shift in K-density for farmers applying organic fertilizers without outsourcing service to the right is not apparent. However, the shift in K-density for farmers applying organic fertilizers with outsourcing services to the right is evident. These

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results indicate that OFA without outsourcing service has no significant effect on the net income of wheat cultivation, whereas OFA with outsourcing service has significant positive effects on the net income of wheat cultivation.

Heterogeneity analysis

We divide the total sample into two subsamples: smallholders managing land less than 3.33 hectares and large-scale farmers managing land of at least 3.33 hectares. MESR is used, respectively, to test the effects of OFA on income across different farm sizes, and the results of ATT are presented in Table 6. OFA with a soil-testing formula increases the net income of wheat cultivation per hectare by 510 RMB for smallholders and 2680 RMB for large-scale farmers. Similarly, OFA with an outsourcing service increases the net income of wheat cultivation per hectare by 640 RMB for smallholders and 4860 RMB for large-scale farmers. It is evident that the income-increasing effect of OFA is more pronounced for large-scale farmers compared to smallholders. Additionally, OFA proves ineffective in increasing income when neither soil-testing formula nor outsourcing service is used with organic fertilizers, aligning with the findings in Table 5.

The test of influence mechanism

The effects of OFA on crop yield and price are tested in order to elucidate the influence mechanism. The results are presented in Table 7. OFA with soil-testing increases wheat yield by 931 kg per hectare, and OFA with outsourcing service increases wheat yield by 1058 kg per hectare. Both of the results are statistically significant at the 1% level. However, neither OFA with soil-testing formula nor OFA with outsourcing service significantly increases the price of wheat.

Discussion

The effectiveness of OFA on increasing income improved by soil-testing formula and outsourcing service

The results of this article reveal that both OFA with soil-testing formulas and OFA with outsourcing services have positive impacts on income. Conversely, the positive impact of OFA on farmers' income is minimized when neither of them is applied. Our results explain why the effectiveness of OFA in enhancing farmers' income remains uncertain in real agricultural production. This is because farmers cannot ensure the effectiveness of technology adoption (Fang et al., 2021). In rural China, most farmers lack professional and systematic training in agricultural knowledge and skills, relying instead on practical experience and social networks for knowledge acquisition (Qin et al., 2022). However, excessive reliance on experiences may lead to knowledge solidification (Li and Li, 2023), making it challenging for farmers to gain valuable knowledge and skills from social networks formed by village acquaintances (Elahi et al., 2021). Therefore, the lack of knowledge and skills results in farmers' inability to use organic fertilizers rationally, which limits the positive impact of OFA on their income (Daadi and Latacz-Lohmann, 2021). As a result, farmers need to rely on external technical support, or even division of labor in order to enhance the effectiveness of OFA (Niu et al., 2022). Fertilizer stations or cooperatives provide soil-testing formulas to enable precise fertilization for farmers (Li et al., 2022*c*). On the other hand, specialization and standardization of fertilization operations can be achieved through the application of outsourcing services (Cui et al., 2022). The Average Treatment Effect on the Treated (ATT) of OFA with outsourcing service exceeds that of OFA with soil-testing formula, indicating that outsourcing service is more effective than soil-testing formula in enhancing the

Table 6. The effects of OFA on income in different levels of farm size

		Treatment group		
Variable	Treat	Real value	Counterfactual value	ATT
NIW (Farm size<3.33 ha)	OFA without soil-testing formula	0.426	0.396	0.030
		(0.017)	(0.009)	(0.021)
	OFA with soil-testing formula	0.487	0.436	0.051***
		(0.017)	(0.012)	(0.017)
	OFA without outsourcing service	0.436	0.428	0.008
		(0.012)	(0.010)	(0.016)
	OFA with outsourcing service	0.486	0.422	0.064***
		(0.027)	(0.014)	(0.018)
NIW (Farm size⩾3.33 ha)	OFA without soil-testing formula	0.568	0.559	0.009
		(0.008)	(0.019)	(0.024)
	OFA with soil-testing formula	0.903	0.635	0.268***
		(0.011)	(0.020)	(0.023)
	OFA without outsourcing service	0.585	0.590	−0.005
		(0.006)	(0.019)	(0.022)
	OFA with outsourcing service	1.065	0.579	0.486***
		(0.023)	(0.032)	(0.036)

Note. Standard errors are reported in parentheses, and *, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

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Table 7. The test of influence mechanism

Variable	Treat	Treatment group		
		Real value	Counterfactual value	ATT
YWH	OFA without soil-testing formula	6.444	6.396	0.048
		(0.031)	(0.039)	(0.045)
	OFA with soil-testing formula	6.392	5.461	0.931***
		(0.057)	(0.046)	(0.065)
	OFA without outsourcing service	6.386	6.346	0.040
		(0.031)	(0.032)	(0.039)
	OFA with outsourcing service	6.501	5.443	1.058***
		(0.076)	(0.061)	(0.085)
PWA	OFA without soil-testing formula	0.047	−0.116	0.163
		(0.005)	(0.007)	(0.214)
	OFA with soil-testing formula	0.042	−0.290	0.332
		(0.008)	(0.002)	(0.227)
	OFA without outsourcing service	0.048	−0.139	0.187
		(0.008)	(0.006)	(0.127)
	OFA with outsourcing service	0.091	−0.232	0.323
		(0.005)	(0.007)	(0.333)

Note. Standard errors are reported in parentheses, and *, ** and *** means passing the test at the significance levels of 10%, 5%, and 1%, respectively.

income-increasing effectiveness of OFA. This suggests that introducing division of labor in the fertilization process is more beneficial for improving fertilization efficiency compared to providing soil-testing formulas to farmers (Slaton et al., 2022). Soil-testing formulas are by no means infallible. For example, soil *K* testing is seriously flawed because the exchangeable fraction estimated by NH4OAc extraction does not necessarily equate to plant-available *K* (Das et al., 2022). Despite fertilizer recommendations based on soil testing being provided to farmers, farmers ultimately remain the decision-makers and implementers of production. This means that the effectiveness of OFA in increasing income may still be compromised by poor decisions made by farmers (Antwi-Agyei and Stringer, 2021). For example, farmers may distrust soil-testing formulas and refuse to adhere to the recommended fertilizer amounts, thereby potentially reducing the effectiveness of OFA due to improper operations (Wu, Li, and Ge 2022). With the implementation of outsourcing services, professional organizations take over agricultural production tasks from farmers, introducing a division of labor into the industry. Through this division of labor, the shortcomings in farmers' production capacity can be addressed, facilitating more rational fertilization practices. Empirical studies have already demonstrated that outsourcing services help reduce excessive fertilizer usage and enhance fertilization efficiency (Rahman and Connor, 2022).

The effectiveness of OFA on increasing income stronger in large-scale farmers than in smallholders

OFA with soil-testing formulas and outsourcing services both have a more significant impact on income for large-scale farmers compared to smallholders. Firstly, large-scale farmers stand to benefit more from technological advancements than smallholders, thus they are more motivated to enhance technology application (O'Connor et al., 2021). Secondly, large-scale farmers have more human and social capitals than smallholders (Chen, Fu, and Liu, 2022), resulting in a higher capacity for technology adoption (Mao et al., 2021). Thirdly, large-scale farmers experience less land fragmentation than smallholders, leading to reduced fertilizer wastage and thereby enhancing the effectiveness of OFA in increasing income (Zhang et al., 2022).

The effectiveness of OFA on increasing income derived from yield-increase rather than price-increase

Our results suggest that both OFA with soil-testing formula and OFA with outsourcing service positively impact crop yield rather than price, and this finding holds true across subsamples of large-scale farmers and smallholders. Comparing our results with other studies reveals that OFA neither drives increases in grain prices (Li et al., 2022*c*) nor in cash crop prices (Su, Zhou, and Zhou, 2022). Although OFA helps contributes to improving product quality, transitioning from high quality to high prices faces several institutional barriers (Fertahi et al., 2021). Firstly, the agricultural product market exhibits characteristics of information asymmetry (Seifert, Kahle, and Hüttel, 2021). Due to the absence of effective standards for product quality classification and labeling systems (Abate et al., 2021), consumers find it challenging to assess the quality of agricultural products. Consequently, they are reluctant to pay higher prices for potentially high-quality products (He and Shi, 2021). Secondly, high transaction costs make it difficult for farmers to sell their products directly to consumers (Foster and Rosenzweig, 2022). Specifically, the difficulty in identifying consumers' preferences for high-quality products results in high search costs, while the uncertainty surrounding product quality complicates price negotiations. In order to save transaction costs, most farmers opt to await middlemen's visits to purchase

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their products (Ali et al., 2021). As a result, the premium generated by product quality improvement is occupied by the middlemen (Sharma et al., 2021). Thirdly, farmers lack bargaining power in the market (Kopp and Mishra, 2022). Since individual farmers occupy a small market share, they often have no advantages in price negotiation (Rogers et al., 2021).

Concluding remarks

The main conclusions are that both OFA with soil-testing formulas and OFA with outsourcing services effectively increase farmers' income. The effectiveness of OFA with outsourcing services is stronger than that of OFA with soil-testing formulas. However, OFA does not increase income if neither soil-testing formulas nor outsourcing services are available. The mechanism through which OFA enhances farmers' income is by boosting crop yields, yet it does not impact product prices. While OFA effectively increases the income of large-scale farmers, it does not have the same effect on smallholders' income.

There are several policy implications drawn from this article. Firstly, the agricultural technology extension system in China requires further enhancement. The extension of organic fertilizers, soil-testing formulas, and outsourcing services should not operate independently but rather be integrated into a comprehensive extension framework. This integration can be achieved through the design of interconnected subsidies, technical training, and other policies. Secondly, the government needs to consider the challenges farmers encounter in responding to the extension of organic fertilizers. Both the accuracy of soil-testing formulas and the quality of outsourcing service should be enhanced to support the application of technology by farmers. Thirdly, eliminating the information asymmetry of agricultural product quality is crucial to unlock the price-increase effect of OFA. The government should establish quality classification standards for various agricultural products and expand existing quality labels, such as pollution-free, green, organic products, and origin labels, to enhance the richness of quality information. In addition, Internet of Things technology should be integrated into the agricultural product circulation system to enhance product traceability. Fourthly, land-scale operations need to be extended to enhance the effectiveness of technology application. The government should implement measures to further promote land transfer in rural China. Some innovative modes of land transfer should be introduced to incentivize smallholders to lease out their land. Expanding the practice where smallholders rent their land in exchange for shares should be prioritized. Additionally, supportive policies, including subsidies and technical training, should be implemented to encourage capable farmers to engage in land rental for scaled operations.

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