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Does Outsourcing Service Reduce the Excessive Use of Chemical Fertilizers in Rural China? The Moderating Effects of Farm Size and Plot Size

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Abstract: The excessive use of chemical fertilizers (OCF) is one of China's main sources of agricultural nonpoint source pollution. It is debatable whether outsourcing service adoption (FOS) reduces OCF. This article argues that farm size and plot size can moderate the effectiveness of FOS in reducing OCF. Particularly, organizations earn more profits when they provide outsourcing services to large-sized farms and plots, thereby preventing their opportunistic behavior and reducing the OCF. Based on the survey data of wheat growers from six major grain-producing counties in Anhui Province, China, the Cobb–Douglas production function is used to measure the OCF, and ordinary least squares (OLS) estimation is used as a benchmark. In addition, propensity score matching (PSM) is used to eliminate the selection bias, and two-stage least squares estimation (IV-2sls) is used to eliminate endogeneity. The results indicate that approximately 90% of the sampled households used excessive fertilizers, signifying that the excessive use of chemical fertilizers in China's agricultural production remains a serious problem. FOS reduces the OCF on large farms and plots. However, the effectiveness of FOS in reducing OCF disappeared when it was provided to small farms and plots. Extending FOS and organizing efficient land transfers should receive equal consideration from policymakers.

Keywords: outsourcing service adoption; excessive use of chemical fertilizers; labor division; farm size; plot size; and moderating effects

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1. Introduction

The purpose of chemical fertilizers is to supplement the soil with nitrogen, phosphorus, potassium, and a variety of essential trace elements for crop growth, thereby increasing crop yield [1]. China's grain production continues to grow as a result of the increased use of chemical fertilizers [2]. Studies show that chemical fertilizers account for 32.2% of the increase in Chinese grain production [3]. Therefore, the Chinese government has provided subsidies to farmers who buy chemical fertilizers since 2006 in order to promote the use of chemical fertilizers by farmers so as to guarantee a steady increase in grain production [4]. Correspondingly, the input of chemical fertilizers increased from 49,277 million kg in 2006 to 52,507 million kg in 2020 [5]. The excessive use of chemical fertilizers (OCF) results in reduced soil quality, soil degradation, and nonpoint source pollution. First, the chemical fertilizers that cannot be absorbed by crops are discharged into the soil, which may result in a reduction in soil quality, such as soil acidification, and a decrease in soil enzyme and microbial activities [6]. In 2019, the proportion of high-quality land in the total farmland was only 31.24% [7]. Second, chemical fertilizers are discharged into rivers through the surface-flow system, causing nonpoint-source pollution [8]. According to the Second National Pollution Source Survey Announcement, the plant-products industry discharged

83,000,000 kg of ammonia nitrogen (8.62% of the total emissions), 719,500,000 kg of total nitrogen (23.66% of the total emissions), and 76,200,000 kg of total phosphorus (24.16% of the total emissions) into the water in 2017. Third, OCF increases the production costs of farmers and decreases land productivity by reducing the quality of the soil [9].

The Chinese Ministry of Agriculture and Rural Affairs issued a document aiming to cease the increase in the use of chemicals by 2020 in order to reduce the OCF. Some remarkable results have already been achieved. Since 2016, the use of chemical fertilizers has been decreasing. According to data from the China Statistical Yearbook, the total input of chemical fertilizers in 2020 was 52,507 million kg, a decrease of 7719 million kg from 2015. However, China's chemical fertilizer input was 313.5 kg/ha in 2020, which was still significantly higher than the internationally recognized upper limit warning of 225 kg/ha for chemical fertilizer input and significantly higher than that in Germany (238.7 kg/ha), France (219.4 kg/ha), the United States (206 kg/ha), Spain (139.2 kg/ha), Canada (128.7 kg/ha), and Italy (127.2 kg/ha) [10]. Due to the continued existence of OCF in China, the "No. 1 Document" for 2022 issued by the Chinese Central Government emphasized the need to reduce chemical fertilizer inputs. As a result, this article discusses how to reduce the OCF and aims to provide practical experience for other countries facing the same problem.

It has been argued that smallholder farmers struggle to reduce the OCF since neither the machinery nor guidance on scientific fertilization are available, forcing them to increase the use of chemical fertilizers in order to avoid potential risks [11]. In addition, since small-scale procurement puts smallholders at a disadvantage in price negotiations, the techniques aimed at reducing the OCF, such as organic fertilizers and formula fertilization by soil testing, are too expensive for smallholders to be widely adopted [12]. Therefore, some scholars believe that the reduction of OCF can be accomplished by increasing farm size through land transfer [13]. However, empirical studies have discovered that large-scale farmers also use excessive chemical fertilizers [14]. Therefore, it is argued that neither smallholders nor large-scale farmers can attain the goal of reducing the OCF if they control the entire agricultural production process [12].

In recent years, the emergence of outsourcing services has alleviated the dilemma of inadequate agricultural labor resources and the division of labor by outsourcing some or all links of agricultural production to service organizations such as cooperatives, agricultural machinery stations, and farmers with agricultural machinery to increase production efficiency [10]. It is argued that OCF can be reduced through the use of outsourcing services in fertilization (FOS), which replace rural households with service organizations in the fertilization process [15]. The emergence of outsourcing services is a practical case of increasing productivity through the division of labor. In addition, it was believed that service organizations have advantages over farmers in the following aspects [15]. First, the achievements of service organizations in chemical fertilizer reduction are highly related to their credit, and they are motivated to reduce the OCF in order to improve their credit, thereby attracting more customers and winning preferential government policies, such as subsidies [16]. Second, service organizations often use mechanized fertilization, which allows crops to absorb nutrients from fertilizers more efficiently than manual fertilization [17,18]. Third, service organizations accumulate a large amount of "hidden" information about the soil through countless practices, and they are able to identify the quality of fertilizers due to their dominance in the fertilizer market [19]. Fourth, service organizations are able to purchase organic fertilizer at a lower price than farmers due to their large-scale procurement. Also, many service organizations are capable of conducting fertilizer response trials with varying fertilizer rates, and fertilizer recommendations based on soil testing can be made, thereby improving the precision of fertilizer application [20]. A large number of studies suggest that FOS helps reduce the OCF. However, some studies concluded that FOS exacerbates the OCF [21]. First, farmers may exert pressure on service organizations to use more chemical fertilizers in order to avoid potential production losses [22]. Second, service organizations may exhibit opportunistic behavior when providing outsourcing services [23]. Service organizations may conspire with fertilizer dealers to increase their sales of chemical fertilizers in return for extra revenue, resulting in OCF [24]. On the other hand, service organizations may reduce service quality in order to save costs since the process of providing outsourcing services is difficult to monitor [12]. There are also some studies that found no significant correlation between FOS and OCF [25].

Previous studies presumed that the relationship between FOS and OCF was linear. However, their conclusions were diametrically opposed. The innovation of this article lies in challenging the assumption of a linear relationship between FOS and OCF. Our hypothesis is that farm size and plot size can moderate the efficacy of FOS in reducing OCF. In fact, providing outsourcing services to large-sized farms and plots results in higher profits for service organizations than providing these services to small-sized operations, which prevents their opportunistic behavior and increases the efficacy of FOS in reducing OCF [26]. Therefore, the effectiveness of FOS in reducing OCF can be enhanced by increasing the farm size and plot size. The research objective of this article is to determine whether the effectiveness of FOS in reducing OCF increases as farm size and plot size increase.

2. Theoretical Analysis

Theoretically, the objective of service organizations providing outsourcing services is to attain maximum profit. Lack of profits causes service organizations to engage in opportunistic behavior, which reduces the efficacy of FOS in reducing the OCF. The increase in farm size and plot size enables service organizations to increase their profits through outsourcing services, thereby preventing their opportunistic behavior. Therefore, the effectiveness of FOS in reducing OCF can be enhanced when providing outsourcing services to large farms and plots. The influence mechanism of FOS on the OCF is shown in Figure 1.

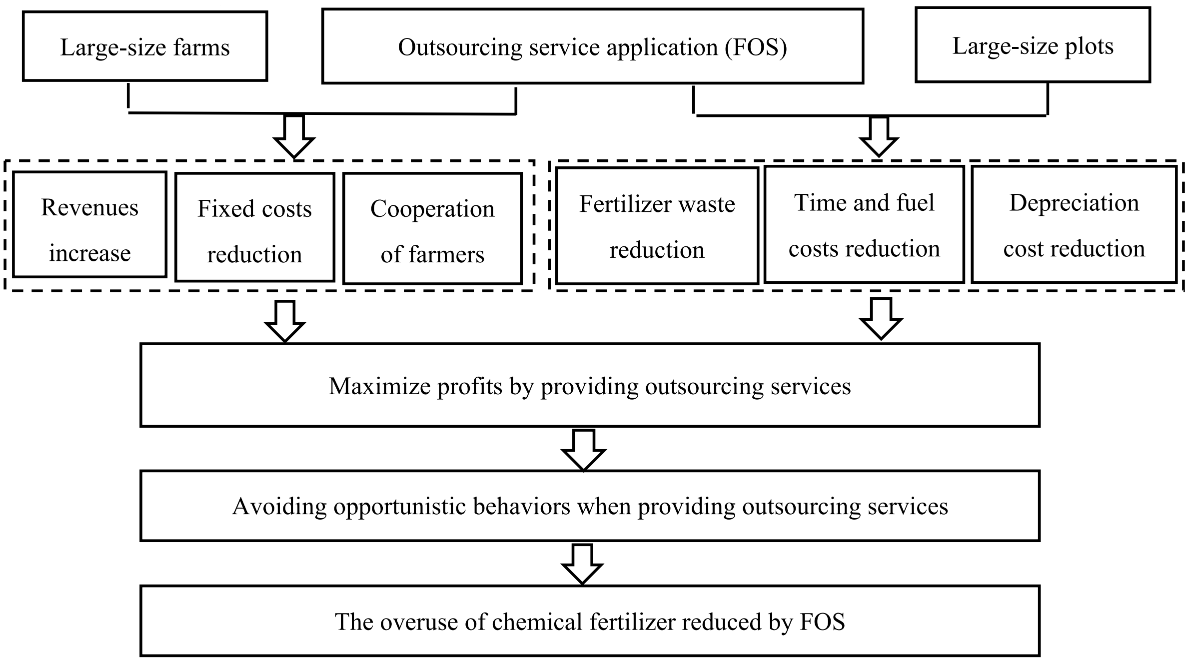

Figure 1. The influence mechanism of outsourcing service application on the excessive use of chemical fertilizers.

2.1. Lack of Profits Results in the Opportunistic Behavior of Service Organizations

In recent years, a large number of Chinese farmers have moved to cities to engage in nonagricultural work and even to reside there, resulting in the abandonment of much arable land and the endangering of food security [27,28]. The Chinese government urges service organizations to provide more services in order to prevent farmland abandonment [29]. In general, service organizations strive to maximize profits, which fosters their opportunistic behavior if they are unable to attain enough profits by providing outsourcing services [25]. These opportunistic behaviors include conspiring with fertilizer distributors to sell more chemical fertilizers in order to increase profits and reducing the quality of services in order to save costs, both of which inhibit the FOS from reducing the OCF and may even exacerbate it [25]. It has been proven that networks in rural China, such as kinship and friendship networks, have a strong effect on preventing opportunistic behavior and that service organizations need to comply with local social norms to achieve a good social reputation [30]. However, the failure to achieve expected profits still results in opportunistic behavior by service organizations and reduces the effectiveness of FOS in reducing OCF [31].

2.2. Profits Generated by Providing Outsourcing Services to Large Farms

Profitable service organizations can provide outsourcing services to large farms. First, service organizations cannot anticipate bidding up prices for providing outsourcing services since high prices may reduce farmers' demand [32]. Therefore, providing services to large farms increases the revenue of service organizations [33]. Second, providing outsourcing services to large farms helps service organizations reduce their average fixed costs [34]. Service organizations need to pay fixed costs in the process of providing services, such as the costs of transporting machinery to the farmland, which can be quite high if service organizations need to provide services over long distances. However, small farms result in very high average fixed costs [34]. Third, smallholders lack farming expertise and are generally risk-averse. Thus, they often require service organizations to increase chemical fertilizers in order to prevent losses [35]. On the contrary, large-scale farmers are more professional in agricultural production than smallholders, and they tend to encourage service organizations to reduce the OCF in order to save costs [36]. Therefore, when service organizations provide outsourcing services to large farms, they make enough profits, their potential opportunistic behavior can be effectively curbed by the increase in profits, and the effectiveness of FOS in reducing OCF can be enhanced. The proposed hypothesis is as follows:

Hypothesis 1 (H1). *The effectiveness of FOS in reducing OCF can be enhanced by increasing the size of the farm. In particular, FOS cannot reduce the OCF on small farms but can reduce the OCF on large farms.*

2.3. Profits Generated by Providing Outsourcing Services to Large Plots

The increase in plot size reduces land fragmentation, which enhances the operational environment for service organizations to provide outsourcing services, thereby increasing the profitability of service organizations through cost savings. First, operating on large plots enables fertilizer to be applied more evenly than operating on fragmented plots, allowing crops to absorb fertilizer more efficiently, thus reducing fertilizer waste and saving costs for service organizations [37]. Second, machinery and labor do not need to move back and forth between scattered plots when service organizations operate on large plots, saving time and fuel costs for service organizations [38]. Third, frequent starting and braking of machinery can be avoided when service organizations operate on large plots rather than fragmented plots, thereby reducing the wear and tear of machinery and the depreciation cost of machinery [39]. It helps save costs when service organizations provide outsourcing services on large plots, which allows them to make more profits. Therefore, the increase in profits can suppress the opportunistic behavior of service organizations and enhance the effectiveness of FOS in reducing the OCF. This article proposes the following hypothesis:

Hypothesis 2 (H2). *The effectiveness of FOS in reducing the excessive use of chemical fertilizers can be enhanced by increasing the size of the plots. Specifically, FOS cannot reduce OCF on small plots but can reduce OCF on large plots.*

3. Data and Methods

3.1. Econometric Model and Variable Selection

We developed a benchmark model with the interactions introduced as the key independent variables to test H1 and H2. The model can be presented as Equation (1), which was estimated using least squares estimation (OLS). OLS is widely used to explain causality between variables due to its simple and efficient computation.

$$EUF_{\mathrm{i}} = \beta_0 + \beta_1 WFO_i + \beta_2 WFO_i \times FIZ_i + \beta_3 WFO_i \times PIZ_i + \beta_4 Z_i + \varepsilon_{2i} \quad (1)$$

The dependent variable is "the excessive use of chemical fertilizers in wheat production per ha of land (EUF)", representing the OCF. The key independent variable is "whether outsourcing services are used in fertilization (WFO)". Two dummy variables are chosen to represent farm size and plot size, and they are "whether farm size is at least 3.33 ha (FIZ)" and "whether the average plot size is at least 3.33 ha (PIZ)". Based on the standards set by the Chinese Ministry of Agriculture and Rural Affairs, farms that are not less than 3.33 ha in a two-harvest area are considered large. In addition, Anhui Province, our study site, belongs to the area of two harvests per year; therefore, we chose 3.33 ha as the standard to distinguish large farms from small ones. The other two key independent variables include "the interaction of WFO and FIZ ($WFO \times FIZ$)" and "the interaction of WFO and PIZ ($WFO \times PIZ$)". Z represents controlled variables that may affect the OCF. The household head's characteristics are considered to impact the OCF, and the variables include "the age of the household head (AGE)", "the gender of the household head (GEN)", "education years of household head (EDU)", "times of technical training received last year (TRA)", "risk preference of household head (RPH)", and "whether the household head has ever been a village cadre (HVC)" [26]. A family's characteristics may affect the OCF, and the variables include "per capita household income (PHI)", "the number of household labor forces (NHL)" and "the ratio of off-farm income to the total household income (ROF)". The farmland's characteristics may affect the OCF, and the variables include "FIZ", "PIZ", "the ratio of high fertile land to the total land (FLA)", and "the average distance between plots and houses (DLH)" [12]. The use of organic fertilizers and formula fertilizers may reduce the OCF, and the variables include "whether organic fertilizer is used (WOA)" and "whether formula fertilizer is used (WFA)" [40]. The variable "whether outsourcing service is used in at least one production link (WAO)" is chosen to replace "WFO" in Equation (1) to test robustness, since outsourcing services of other production links may affect fertilization and the cost of purchasing services may reduce the budget of purchasing fertilizers, thereby reducing the use of fertilizers [41].

It may be these factors, rather than the FOS, that affect the OCF, since the FOS is not a random event that is decided by some specific factors. However, the results of OLS may mislead us about the causal relationship between the FOS and the OCF [42]. Propensity score matching (PSM) is used to eliminate the selection bias due to the variable's nonrandom nature "WFO" by constructing a counterfactual analysis framework [43–45]. Farmers that are adopting outsourcing services are in the treatment group, while the ones that are not adopting outsourcing services are in the control group. The first step of PSM calculates the probability of adopting outsourcing services by using the probit model [43–45], then farmers from the treatment group are matched with those from the control group. The latter is considered as the counterfactual result of the former, which are the excessive chemical fertilizer users who adopt outsourcing services under the assumption of not adopting outsourcing services [45]. The average treatment effect on the treated (ATT) is calculated by Equation (2), EUF_{i1} represents the excessive chemical fertilizers of farmers in the treatment group who adopt outsourcing services. Their counterfactual results are represented by EUF_{io}, and the result of ATT indicates the effect of FOS on the OCF [46].

$$ATT = E(EUF_{i1} - EUF_{i0} | WFO_i = 1) \quad (2)$$

Despite the fact that PSM helps solve the problem of selection bias, it cannot solve the problem of endogeneity due to reverse causation [45]. Since other factors that impact OCF may be missed in the model and the OCF may prompt farmers to buy outsourcing services, "*WFO*" may be an endogenous variable [47]. The least squares estimation of two stages (IV-2sls) is always used to solve the problem of endogeneity, while the most critical step is to determine the right instrumental variable (IV). The IV, being highly correlated with the endogenous variable but uncorrelated with the dependent variable, is always chosen to solve the problem. Providing outsourcing services to distant farmers will increase the fixed cost of service organizations, and they will have to charge higher prices from farmers or refuse to provide outsourcing services, both of which prevent farmers from obtaining outsourcing services [48]. However, the distance between service organizations and farmers is uncorrelated with the OCF [49]. Therefore, the variable "the nearest distance between farmers and service organizations (*DFO*)" is chosen as the instrumental variable for "*WFO*". The IV-2SLS is used to estimate Equations (3) and (4). The instrumental variable (*DFO*) is used to estimate "*WFO*" in Equation (3), and the estimated value of "*WFO*" ($W\hat{F}O$) is substituted into Equation (4) to eliminate the bias caused by the endogeneity of "*WFO*". Since "*WFO*" is included in the two interactions, "$DFO \times FIZ\lozenge$" and "$DFO \times PIZ\lozenge$" are also the instrumental variables for "$WFO \times FIZ\lozenge$" and "$WFO \times PIZPIZ$" when estimating the moderating effects of "*FIZ*" and "*PIZ*" by the total sample.

$$WFO_i = \vartheta_0 + \vartheta_1 DFO_i + \vartheta_2 FIZ_i + \vartheta_3 PIZ_i + \vartheta_4 Z_i + \varepsilon_{3i} \tag{3}$$

$$EUF_i = \mu_0 + \mu_1 W\hat{F}O_i + \mu_2 FIZ_i + \mu_3 PIZ_i + \mu_4 Z_i + \varepsilon_{4i} \tag{4}$$

The Cobb–Douglas production function is widely used to describe the relationship between inputs and outputs. In this article, we also created a Cobb–Douglas production function to calculate the yield elasticity of chemical fertilizer and derive the "*EUF*". The equation is shown as Equation (5).

$$\ln y_i = \alpha_0 + \alpha_1 \ln F_i + \alpha_2 \ln L_i + \alpha_3 \ln M_i + \alpha_4 \ln S_i + \alpha_5 \ln O_i + \alpha_6 WAO_i + \alpha_7 Z_i + \varepsilon_{1i} \tag{5}$$

The variables measuring input and output are introduced in Equation (5) by referring to previous studies. y represents the wheat yield per ha of land. F represents the use of chemical fertilizer per ha of land. L represents the input of labor per ha of land. M represents the machinery expenses per ha of land. S represents the seedling expenses per ha of land. O represents other expenses per ha of land, excluding fertilizers, labor, machinery, and seedlings. Outsourcing services may affect the crop yield, and the variable "*WAO*" is introduced in Equation (5). Z represents controlled variables.

This article assumes that farmers take profit maximization as their production goal, and the marginal effect of fertilizers on grain output should be equal to the ratio of fertilizer price (P_F) to wheat price (P_y). Therefore, the optimal chemical fertilizers used in wheat production (OUF) can be measured as Equation (6).

$$OUF_i = \frac{\alpha_1 \times y_i}{p_F / p_y} \tag{6}$$

In Equation (6), P_F and P_y represent the price of chemical fertilizer and wheat product, respectively. The excessive use of chemical fertilizers in wheat production per ha of land (EUF) can be measured by Equation (7).

$$EUF_i = F_i - OUF_i \tag{7}$$

3.2. Study Site

This study was carried out in Anhui Province, China, in 2021. Anhui is one of the six most important grain-producing provinces in the Eastern China. Data from China Statistical Yearbook indicates that Anhui Province's grain production was 40,876 million kg in 2021, ranking fourth among all the provinces in China. Six main grain-producing counties are selected in Anhui Province, and three of them are located north of the Huai River, including Funan County, Lixin County, and Yongqiao County, where wheat and maize are the main crops. Three counties are located south of the Huai River and north of the Yangtze River, including Feixi County, Mingguang County, and Dingyuan County, where rice and wheat are the main crops. The geographic locations of the sample counties are shown in Figure 2.

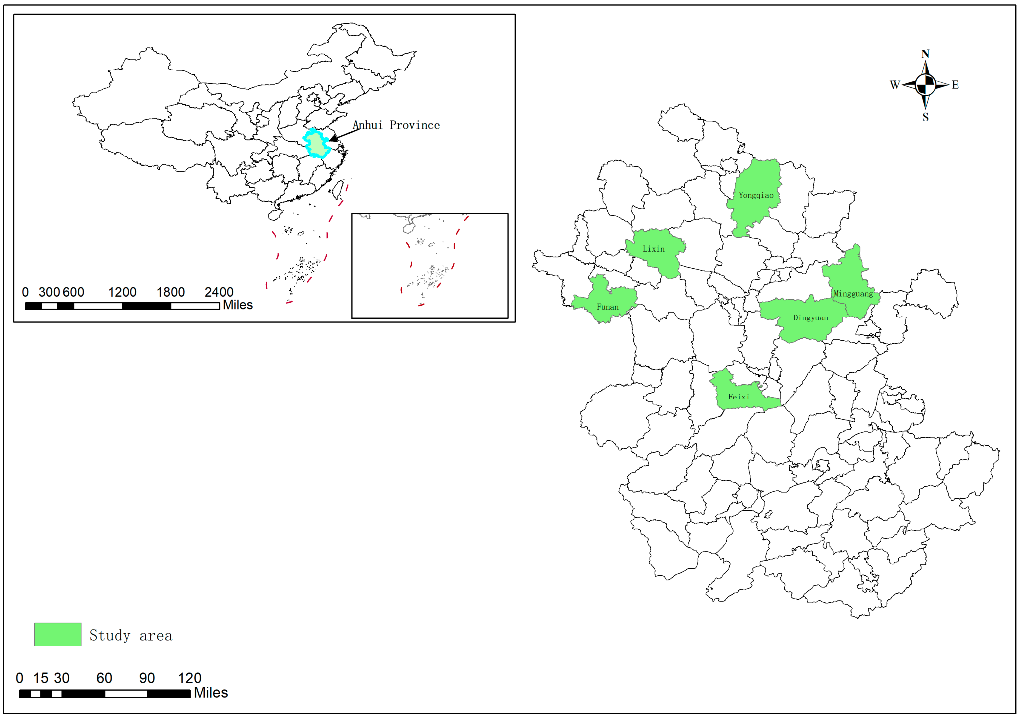

Figure 2. Location of Anhui Province and the province's six grain-producing counties that comprise the study sites.

3.3. Data

Data were collected through a 2021 survey of grain-growing households located in Anhui Province. Both multistage clustered random sampling and stratified random sampling methods were used to generate household samples. First, six major grain-producing counties were chosen as the study's locations. Second, one township with a high per capita income and one with a low per capita income were selected in each sample county. Third, one village with a high per capita income and one with a low per capita income were selected in each sample township. Fourth, in each village, 10 samples were taken from farmers whose farms are not less than 3.33 ha, and the other 10 samples were taken from farmers whose farms are less than 3.33 ha. This sampling strategy resulted in the selection of 480 households for surveying (24 villages in 12 towns in 6 counties), including 240 large-scale farmers with a minimum farm of 3.33 ha and 240 smallholders with a maximum farm of 3.33 ha. Due to the fact that 10 households did not grow wheat, a total of 470 samples, including 240 large-scale farmers and 230 smallholders, were used. The survey involved a questionnaire with the household head, and the questionnaire was administered through face-to-face interviews between our researchers and the household head. We primarily asked about the input and output of agricultural production and whether they used FOS for each production link. In addition, we asked the farmers about their personal and family conditions, such as their age, education years, risk preference, number of family members, family income, and so on. Limited data coverage and sample size may be the potential limitations of the dataset.

4. Results

4.1. Descriptive Statistics of Variables

The descriptive statistics of variables are reported in Table 1. The results indicated that the average amount of fertilizer used was 968.19 kg/ha per household, which was significantly higher than the internationally recognized maximum limit warning for chemical fertilizer input of 225 kg/ha. The largest portion of total costs comprised machinery and chemical fertilizer, indicating that the rising cost of labor forces induces the substitution of capital for labor forces. In total, 50% of the sampled households used outsourcing services for at least one production link, but only 28% of them used outsourcing services for fertilization.

Table 1. The descriptive statistics of variables.

Variable Name	Variable Definition	Mean	Var	Min	Max
The wheat yield per ha of land (y)	Unit: kg/ha	6188.93	1295.84	3750	9000
The use of chemical fertilizer per ha of land (F)	Unit: kg/ha	968.19	293.2	225	2250
The input of labor per ha of land (L)	Unit: days/ha	10.37	13.76	0.3	107.85
The machinery expenses per ha of land (M)	Unit: RMB/ha	2539.6	1849.06	150	7800
The seedling expenses per ha of land (S)	Unit: RMB/ha	1245.47	437	150	3000
Other expenses per ha of land (O)	Unit: RMB/ha	798.29	552.31	75	4500
Price of wheat product (P_y)	Unit: RMB/kg	2.09	0.34	0.8	3.74
Price of chemical fertilizer (P_F)	Unit: RMB/kg	2.6	0.8	0.43	8.5
Whether outsourcing services are used in fertilization (*WFO*)	0 = No, 1 = Yes	0.28	0.45	0	1
Whether outsourcing services are used in at least one production link (*WAO*)	0 = No, 1 = Yes	0.5	0.5	0	1
Age of household head (*AGE*)	2020-Birth year	50.27	8.85	27	76
Gender of household head (*GEN*)	0 = female, 1 = male	0.89	0.31	0	1
Education years of the household head (*EDU*)	computation from primary school	8.57	2.99	0	16
Times of technical training received last year (*TRA*)		1.92	2.19	0	20
Risk preference of the household head (*RPH*)	0 = Risk aversion, 1 = Risk neutrality, 2 = Risk appetite	0.93	0.88	0	2
Whether the household head has ever been a village cadre (*HVC*)	0 = No, 1 = Yes	0.29	0.46	0	1
Per capita household income (*PHI*)	Unit: RMB 1000	3.77	5.52	0.1	70
The number of household labor forces (*NHL*)		3.37	1.43	1	10
The ratio of off-farm income to the total household income (*ROF*)		0.4	0.33	0	0.99
Whether the size of the farm is at least 3.33 ha (*FIZ*)	0 = No, 1 = Yes	0.51	0.5	0	1
Whether the average size of plots is at least 3.33 ha (*PIZ*)	0 = No, 1 = Yes	0.43	0.49	0	1
The ratio of high fertile land to the total land (*FLA*)		0.63	0.44	0	1
The average distance between plots and houses (*DLH*)	The mean value of the farthest and nearest distance. Unit: km	0.89	0.85	0.01	6
Whether organic fertilizer is adopted (*WOA*)	0 = No, 1 = Yes	0.2	0.4	0	1
Whether formula fertilizer is adopted (*WFA*)	0 = No, 1 = Yes	0.39	0.49	0	1
The nearest distance between farmers and service organizations (*DFO*)	Instrumental variable. Unit: km	5.28	4.3	0.1	30

Note: Var means standard variance. Min means the minimum value. Max means the maximum value.

4.2. The Results of the Cobb–Douglas Production Function

The estimated results of the Cobb–Douglas production function are reported in Table 2. Wheat yield per ha of land increases by 0.1162% if the input of chemical fertilizers per ha (F) of land increases by 1%, and by 0.0433% if the machinery expenses per ha of land (M) increase by 1%. Both of the two results are statistically significant at the 1% level. The output elasticity of labor (L) is negative, which means that there is an excess of labor input. The output elasticity of other output (O) is also negative, as pesticide expenses account for the largest proportion of other inputs. Pesticides are used to prevent yield loss caused by pests and diseases rather than to increase yields. In the control variables, the yield per ha of land on large farms is significantly lower than that on small farms, which is consistent with the results of previous studies, as large-scale farmers seek to maximize profits while smallholders seek to maximize yields [48]. The yield per ha of land on large plots is significantly lower than that on small ones due to the fact that increasing plot size facilitates mechanized farming and the development of farmland infrastructure [49]. The variables "*AGE*" and "*DLH*" have significant negative effects on wheat yields, whereas "*EDU*", "*RPH*", and "*HVC*" have significant positive effects on wheat yields. The "excessive chemical fertilizers per ha of land (*EUF*)" is measured, and the statistical results indicate that 415 sample households used excessive chemical fertilizers, accounting for 88.3% of the total samples. The average amount of excessive chemical fertilizers used per household is 325.69 kg/ha, and the maximum amount is 1866.54 kg/ha.

Table 2. The estimated results of the Cobb–Douglas production function.

Variables	Marginal Effect	Standard Error	t Value	*p* Value
Ln*F*	0.1162 ***	0.0306	3.80	0.000
ln*L*	−0.0198 **	0.0092	−2.14	0.033
ln*M*	0.0433 ***	0.0118	3.68	0.000
ln*S*	0.0265	0.0241	1.10	0.273
ln*O*	−0.0388 ***	0.0144	−2.69	0.007
WAO	0.0226	0.0184	1.23	0.220
AGE	−0.0022 *	0.0012	−1.76	0.079
GEN	−0.0448	0.0302	−1.49	0.138
EDU	0.0093 ***	0.0035	2.62	0.009
TRA	−0.0048	0.0046	−1.06	0.288
RPH	0.0451 ***	0.0125	3.62	0.000
HVC	0.0383 *	0.0217	1.77	0.078
PHI	0.0025	0.0018	1.43	0.155
NHL	0.0088	0.0067	1.33	0.185
ROF	−0.0243	0.0293	−0.83	0.408
FIZ	−0.0781 **	0.0364	−2.15	0.032
PIZ	0.0667 *	0.0355	1.88	0.061
FLA	−0.0136	0.0218	−0.63	0.532
DLH	−0.0201 *	0.0113	−1.78	0.075
WOA	−0.0328	0.0241	−1.36	0.175
WFA	0.0025	0.0203	0.13	0.900
cons	7.6796 ***	0.3031	25.34	0.000
F value	6.55 ***			
Prob > F	0.0000			
Adj R^2	0.1990			
Observations	470			

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

4.3. The Estimated Results of the Benchmark Model

The estimated results of Equation (1) are reported in Table 3. All of the models passed the F test at the 1% level of significance, indicating that they all fit well. The marginal effect of "*WFO*" on "*EUF*" is significantly positive at the 5% level when only "*WFO*" is introduced to the model. However, the marginal effect of "*WFO*" does not pass the t test when other key independent variables, including "*FIZ*", "*PIZ*", and their interactions with "*WFO*", are introduced to the model. Furthermore, it still does not pass the t test after the controlled variables are introduced to the model. These results indicate that the relationship between FOS and OCF may not be linear. The marginal effects of "$WFO \times FIZ\Diamond$" and "$WFO \times PIZ\Diamond$" are both significantly negative at the 5% level. Particularly, FOS was able to reduce excessive chemical fertilizers by 156.4453 kg/ha on large farms and by 187.1256 kg/ha on large plots. These results indicate that the effectiveness of FOS in reducing the OCF was enhanced when outsourcing services were provided to large farms and plots. Therefore, H1 and H2 are verified. In addition, the enhancement moderating effect of "*PIZ*" is stronger than that of "*FIZ*". In the control variables, "*PHI*" has a positive effect, while "*EDU*", "*RPH*", "*FLA*", "*WOA*", and "*WFA*" have negative effects, which are consistent with previous studies. "*PIZ*" has a statistically significant negative effect at the 1% level, whereas "*FIZ*" has no significant effects. The results indicate that the OCF cannot be reduced when farm size is increased without increasing plot size.

Table 3. The estimated results of the benchmark model.

Variables	Model (I) Marginal Effect	Model (I) Standard Error	Model (II) Marginal Effect	Model (II) Standard Error	Model (III) Marginal Effect	Model (III) Standard Error
WFO	92.7321 **	39.4092	8.3257	38.9115	−3.1409	38.084
WFO × *FIZ*	—	—	−160.9876 **	80.2253	−156.4453 **	78.3019
WFO × *PIZ*	—	—	−215.5429 **	85.6975	−187.1256 **	84.6915
AGE	—	—	—	—	3.0943	2.1666
GEN	—	—	—	—	−47.7837	53.7597
EDU	—	—	—	—	−11.1312 *	6.2843
TRA	—	—	—	—	11.1011	8.1014
RPH	—	—	—	—	−79.0625 ***	21.9136
HVC	—	—	—	—	−13.498	38.8334
PHI	—	—	—	—	6.3371 **	3.1493
NHL	—	—	—	—	10.4725	11.9359
ROF	—	—	—	—	−17.7573	51.9941
FIZ	—	—	—	—	56.5364	70.3905
PIZ	—	—	—	—	−257.2754 ***	72.0057
FLA	—	—	—	—	−78.1852 **	39.0084
DLH	—	—	—	—	2.1849	19.9931
WOA	—	—	—	—	−81.5141 **	43.7832
WFA	—	—	—	—	−55.4042	37.2566
cons	299.4522 ***	20.964	330.3596 ***	26.6656	363.2798 **	149.4944
F value	5.54 **		13.51 ***		6.64 ***	
Prob > F	0.0190		0.0000		0.0000	
Adj R^2	0.0096		0.1177		0.1778	
Observations	470		470		470	

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

4.4. The Estimated Results of Subsamples

The estimated results of Equation (2) are reported in Table 4. All of the models passed the F test at the 1% significance level, indicating that they all fit well. FOS reduces the excessive use of chemical fertilizers on large farms and plots. Both results are statistically significant at the 1% level, and the effectiveness of FOS in reducing OCF is higher in the "*PIZ* = 1" subsample than in the "*FIZ* = 1" subsample. However, FOS has no significant effect on the OCF for small farms and plots. The estimated results of subsamples are consistent with the benchmark's estimated results.

Table 4. The estimated results of subsamples.

Variables	*FIZ* = 1 Marginal Effect	*FIZ* = 0 Marginal Effect	*PIZ* = 1 Marginal Effect	*PIZ* = 0 Marginal Effect
WFO	−188.3472 ***	74.0237	−216.4149 ***	92.2635
	(34.4291)	(67.7079)	(39.421)	(57.9373)
Controlled variables	Controlled	Controlled	Controlled	Controlled
F value	8.37 ***	4.30 ***	5.85 ***	4.53 ***
Prob > F	0.0000	0.0000	0.0000	0.0000
Adj R^2	0.3161	0.1679	0.2543	0.1645
Observations	240	230	200	270

Note: The standard errors are reported in parentheses. *** mean passing the test at the significance levels of 1%.

4.5. The Estimated Results Using "WAO" Rather Than "WFO"

Robustness is tested by substituting the variable "*WAO*" for "*WFO*" in Equations (1) and (2). The results are presented in Table 5. The adoption of outsourcing services for at least one production link reduced the OCF on large farms and plots. However, its effectiveness in reducing the OCF is lost when outsourcing services are provided to small farms and plots. The estimated results are similar to the benchmark model after using "*WAO*" instead of "*WFO*".

Table 5. The estimated results using "*WAO*" rather than "*WFO*".

Variables	Total Sample Marginal Effect	*FIZ* = 1 Marginal Effect	*FIZ* = 0 Marginal Effect	*PIZ* = 1 Marginal Effect	*PIZ* = 0 Marginal Effect
WAO	−50.0513	−73.4812 **	−87.0485	−85.6135 **	−73.753
	(32.9386)	(32.9488)	(57.8753)	(36.9805)	(51.6567)
$WAO \times FIZ$	−149.0946 *	—	—	—	—
	(77.2679)	—	—	—	—
$WAO \times PIZ$	−187.9035 **	—	—	—	—
	(84.4706)	—	—	—	—
Controlled variables	Controlled	Controlled	Controlled	Controlled	Controlled
F value	6.80	6.08	4.40	3.65	4.49
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
Adj R^2	0.1820	0.2416	0.1720	0.1573	0.1629
Observations	470	240	230	200	270

Note: The standard errors are reported in parentheses. * and ** mean passing the test at the significance levels of 10% and 5%, respectively.

4.6. The Estimated Results of PSM

The propensity score was calculated using the probit model. The wide common support area of the propensity score helps reduce the sample loss, which ensures that the match based on the propensity score works well. The propensity score's probability density can be presented in Figure 3. This article presents only the probability density figure based on the total sample. In addition, the probability density figure based on the subsample can be obtained by contacting the corresponding author. After matching the sample households, the probability density function of the treatment group (farmers adopting outsourcing services) is close to that of the control group (farmers not adopting outsourcing services), indicating that it is a good match. This article applies three matching methods, including neighbor based on the principle that one sample from the treatment group is matched with three samples from the control group, kernel with a bandwidth of 0.06, and local linear regression (LLR) with a bandwidth of 0.8. When the kernel is applied, only one sample from the treatment group is lost. However, no samples are lost when neighbor and llr are applied, so it can be concluded that PSM is ideal for our empirical study.

The results of the balance test are reported in Table 6. Only the results of the balance test based on the total sample are presented. Also, the results of the balance test based on the subsample can be obtained by contacting the corresponding author. Despite the matching method used, all the indicators, including Pseudo R^2, LR chi^2, mean bias, and median bias, are obviously reduced compared with before the matching. The results indicate that the two groups of samples have similar characteristics after the matching, and the balance test could be passed.

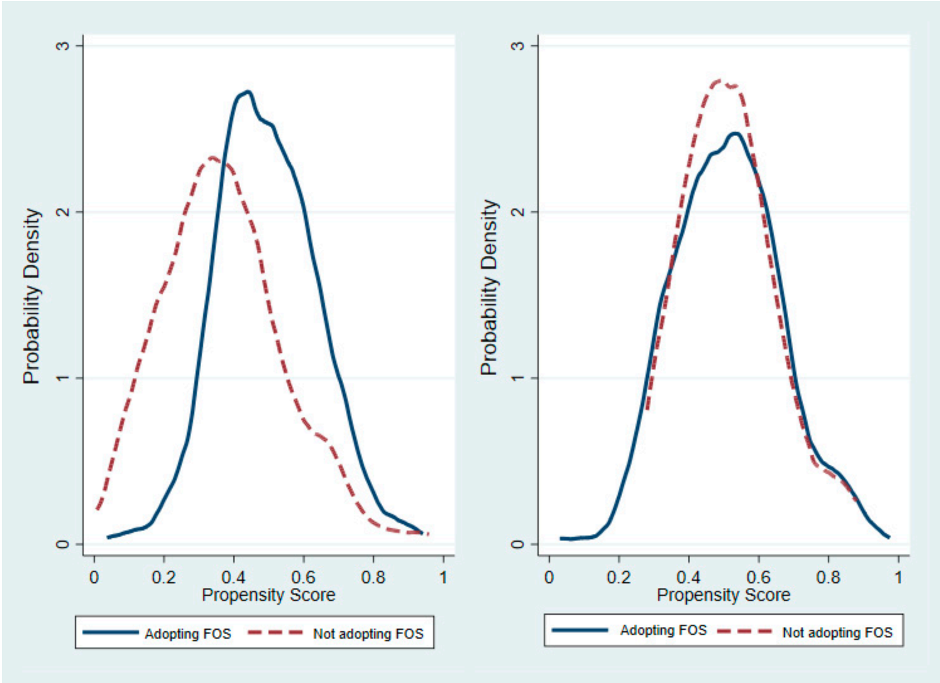

Figure 3. The probability density before and after matching.

Table 6. The balance test's results.

Matching Method	Pseudo R^2	LR Chi^2	p Value	Mean Bias (%)	Median Bias (%)
Unmatched	0.022	12.41	0.258	9.4	7.3
Neighbor	0.005	1.95	0.997	4.9	5.1
Kernal	0.001	0.29	1	1.8	1.5
LLR	0.004	1.56	0.999	3.8	3.4

The estimated results of the average treatment effect on the treated (ATT) are reported in Table 7. The results are based on the total sample of large-sized farms (*FIZ* = 1), small-scale farmers (*FIZ* = 0), large plots (*PIZ* = 1), and small plots (*PIZ* = 0). The results of ATT are estimated with the total sample. The subsamples "*FIZ* = 0" and "*PIZ* = 0" are not statistically significant, indicating that FOS has no effects on the OCF on small farms and plots. However, FOS reduced the excessive chemical fertilizers by 178.1482 kg/ha ~ 194.286 kg/ha on large farms. The results estimated with all three matching methods are statistically significant at the 1% level. FOS reduces excessive chemical fertilizers by 212.0407 kg/ha ~ 252.0445 kg/ha on large-sized plots. The results estimated with all three matching methods are statistically significant at those estimated with the benchmark model.

4.7. The Estimated Results of IV-2sls

The validity of the instrumental variable was tested, and the results are reported in Table 8. Kleibergen Paap rk LM statistic (KPrkLM) rejects the null hypothesis at the 5% level at least, indicating that the endogenous variable (*WFO*) can be effectively identified by the instrumental variables, including "*DFO*", "*DFO* × *FIZ*", and "*DFO* × *PIZ*". Both the Cragg–Donald Wald F statistic (CDWF) and Kleibergen–Paap rk Wald F statistic (KPrkWF) were larger than the critical value of the Stock Yogo weak ID test at the 10% level, which is 16.38, indicating that all the instrumental variables are not weak instrumental variables.

Table 7. The estimated results of ATT.

Sample	Matching Method	Mean Value of Treatment Group	Mean Value of Control Group	ATT	t Value	Observations
Total sample	Neighbor	392.1843	339.4941	52.6902	1.16	470
	Kernal	386.7324	322.6023	64.1301	1.46	
	llr	392.1843	331.2147	60.9696	1.16	
FIZ = 1	Neighbor	203.5525	381.7007	−178.1482 ***	−3.76	240
	Kernal	205.5322	393.8386	−188.3064 ***	−5.21	
	llr	203.5525	397.8385	−194.286 ***	−3.51	
FIZ = 0	Neighbor	423.1925	386.7918	36.4006	0.46	230
	Kernal	418.2828	359.7502	58.5326	0.84	
	llr	423.1925	391.9995	31.1929	0.36	
PIZ = 1	Neighbor	120.8558	372.9004	−252.0445 ***	−4.67	200
	Kernal	143.819	355.8597	−212.0407 ***	−4.97	
	llr	120.8558	350.4653	−229.6094 ***	−4.26	
PIZ = 0	Neighbor	442.4147	317.0595	125.3552	1.3	270
	Kernal	442.4147	346.9622	95.4525	1.58	
	llr	442.4147	338.5488	103.8658	1.08	

Note: ATT means the average treatment effect on the treated. Standard errors are reported in parentheses. *** mean passing the test at the significance levels of 1%.

Table 8. The tests of instrumental variables.

Statistics	Total Sample	*FIZ* = 1	*FIZ* = 0	*PIZ* = 1	*PIZ* = 0
KPrkLM	5.208 **	61.387 ***	59.393 ***	43.873 ***	79.279 ***
p value	0.0225	0.0000	0.0000	0.0000	0.0000
CDWF	22.276	58.638	71.821	40.669	97.852
KPrkWF	22.024	45.685	105.244	39.939	138.216
Observations	470	240	230	200	270

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

The estimated results of IV-2sls are reported in Table 9. Only the results of the second stage of IV-2sls are reported. The results of the first stage can be obtained by contacting the corresponding author. The marginal effects of two interactions are both negative and statistically significant at the 5% level, indicating that the effectiveness of FOS in reducing the OCF is enhanced when it is provided to large farms and plots. FOS reduces the excessive use of chemical fertilizers by 218.1161 kg/ha on large farms. It also reduces the excessive use of chemical fertilizers by 233.299 kg/ha on large plots. However, FOS has no significant effects on the OCF when it is provided to small farms and plots. The results are consistent with the benchmark when the endogeneity is eliminated.

Table 9. The estimated results of IV-2sls.

Variables	Total Sample	*FIZ* = 1	*FIZ* = 0	*PIZ* = 1	*PIZ* = 0
WFO	101.0975	−218.1161 **	78.756	−233.299 **	115.3363
	(638.7516)	(98.5778)	(72.5873)	(118.5104)	(90.0644)
WFO × *FIZ*	−142.5642 **	—	—	—	—
	(67.7933)	—	—	—	—
WFO × *PIZ*	−193.2782 **	—	—	—	—
	(85.2985)	—	—	—	—
Controlled variables	Controlled	Controlled	Controlled	Controlled	Controlled
F value	1.83 **	1.92 **	2.04 **	2.09 **	2.46 ***
Prob > F	0.0196	0.0224	0.0163	0.0461	0.0022
Observations	470	240	230	200	270

Note: The standard errors are reported in parentheses. ** and *** mean passing the test at the significance levels of 5% and 1%, respectively.

5. Discussion

5.1. OCF Reduced by FOS on Large-Sized Farms and Plots

The results indicate that FOS only reduces OCF on large farms and plots, confirming our hypotheses H1 and H2. It also indicates that there is no substantial linear relationship between FOS and OCF, so it would be inappropriate to simply conclude that FOS can reduce or aggravate OCF. Service organizations are able to increase their revenues and save costs by providing outsourcing services to large farms and plots, as well as controlling their opportunistic behaviors. Therefore, the advantages of labor division can be fully maximized on large farms and plots. In addition to restricting opportunistic behavior, large farms and plots provide conducive conditions for the application of FOS, which is particularly conducive to enhancing the effectiveness of mechanized operations, thereby promoting the reduction of OCF. Moreover, since large-scale farmers are often the opinion leaders in the village, they can easily spread the good reputation of service organizations, which encourages them to improve the quality of service on large farms and plots [50]. Increasing the plot size is more important than increasing the farm size since carrying out fertilization operations on contiguous plots can save costs to the greatest extent, helping service organizations generate more profits and inhibit their opportunistic behaviors, thereby enhancing the effectiveness of FOS in reducing OCF [51]. The existence of both large farms and smallholders in rural China provides material for this article to examine the moderating effects of farm size and plot size. As a result, our sample households include farmers with different farm sizes and plot sizes [52].

5.2. OCF Not Increased by FOS on Small-Sized Farms and Plots

FOS does not significantly reduce or increase OCF when it is provided to smallholders. The reason is that in some parts of rural China, smallholders whose plots are adjacent to each other organize to buy outsourcing services uniformly, ensuring that service organizations continue to work on contiguous plots [53]. Therefore, the uniform purchase of outsourcing services by smallholders helps to prevent the loss of profits caused by providing services to individual smallholders, thereby limiting the opportunistic behavior of service organizations. However, our results also indicate that the uniform purchase of outsourcing services is insufficient to activate the effectiveness of FOS in reducing excessive chemical fertilizers among smallholders. The heterogeneity of demand among smallholders makes it difficult to organize the uniform purchase of outsourcing services [54]. First, fertilization has a lower demand for outsourcing services than other production links, such as harvest [55]. Second, since fertilization is considered to be closely correlated with crop yield, risk-aversion may reduce the demand for outsourcing services [56]. It is not difficult to determine that organizing the uniform purchase of outsourcing services by smallholders has positive externalities and that the organizers incur high coordination costs. Therefore, smallholders' uniform purchase of outsourcing services cannot be organized by the market but rather by public organizations such as village committees. Village cadres need to be patient to publicize the benefits of uniformly purchasing outsourcing services from smallholders. On the other hand, the village committee should introduce and endorse as many well-qualified service organizations as possible to increase farmers' trust in the uniform purchase of outsourcing services.

5.3. Land-Scale Management Is the Basis of the Agricultural Division of Labor

Outsourcing is essentially the division of labor in the fertilization process. It has been well documented that division of labor can increase efficiency, which is conducive to reducing the OCF. However, labor division increases both market transactions and transaction costs [57]. Due to the increased frequency of transactions, service organizations incur higher transaction costs when trading with smallholders, thereby reducing their profit margin [51]. Land transfers reduce the number of farmers. In addition, reducing the frequency of service outsourcing transactions cuts transaction costs. Large-scale farmers have stable demand for outsourcing services, making it easier for them to negotiate long-term deals with service organizations [58,59]. Therefore, the potential opportunistic behaviors of service organizations can be restrained by establishing trust and reputation mechanisms in long-term transactions, thus enhancing the effectiveness of labor division [60].

6. Concluding Remarks

The main conclusions include that chemical fertilizers are excessively used in China's agricultural production. Moreover, FOS reduces OCF only on large farms and plots but has no effect on reducing OCF on small farms and plots.

It is inappropriate to discuss the effectiveness of FOS in reducing the OCF in developing countries with a large number of smallholders without taking land fragmentation into account. Therefore, outsourcing services and land transfer are not two alternative but complementary policies for reducing the OCF. Both of them should be encouraged simultaneously. It is necessary to extend the outsourcing service market to both demand and supply. The government should disseminate knowledge of scientific fertilization to farmers in order to reduce their concerns regarding FOS, thereby increasing their demand for outsourcing services. Some preferential policies, such as subsidies, should be given to attract more service organizations to provide outsourcing services. The local government should also provide outsourcing services if the service organization is not sufficient to meet the demand of FOS. Alternatively, land transfer should be encouraged, and both farm and plot sizes should be increased. The local government should mobilize village committees to integrate the scattered plots of land waiting to be leased into contiguous plots of land. Formal land transfer contracts should be encouraged to reduce the uncertainty of land transactions. Lastly, information platforms should be established in villages to reduce the information asymmetry of land transactions.

Since the rural land market is underdeveloped, other developing countries besides China also face the problem of land fragmentation, which is not conducive to reducing OCF through division of labor such as FOS. The conclusions of this paper have implications for these countries. The uniform purchase of outsourcing services should be organized to combat the negative effects of land fragmentation on FOS. Only individuals or organizations with high authority and a good reputation in the village are capable of effectively coordinating the different demands of outsourcing services among farmers and successfully organizing the uniform purchase of outsourcing services. The improvement of social capital also facilitates the collective action of villagers to purchase outsourcing services, including the enhancement of relationships between villagers, an increase in social trust, and the development of good social norms.

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