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Do Agricultural Machinery Services Facilitate Land Transfer? Evidence from Rice Farmers in Sichuan Province, China

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Abstract: Agricultural machinery services play an increasingly important role in the land transfer market, especially in developing countries. Prior studies have explored the impact factors of machinery use on agricultural production and land transfer, respectively. However, little research has focused on the relationship between the adoption of agricultural machinery services and the land transfer of rice farmers. To bridge this gap, this study investigated the correlation between machinery services and land transfer, using unique survey data of 810 rice farmers collected from Sichuan province in China. Additionally, this study further explored the impact mechanism on land transfer of rural households with IV-Probit and IV-Tobit models. The empirical results show the following: (i) Agricultural machinery services have a significantly positive and robust effect on both the incidence and area of rice farmers' land transfer-in, while the impact degree is different. Specifically, with other conditions remaining unchanged, and with a 1% increase in the proportion of machinery services, the average probability of land transfer-in of rice farmers increased by 2.4%, and the area of land transfer-in increased by 13.4 mu, on average. (ii) For control variables, head education, agricultural certificates and whether the majority of land, are in a flat area have positive impacts on land transfer-in behavior. Yet, age and off-farm labor have a negative impact on land transfer-in area. Moreover, our findings highlight the importance of agricultural machinery services in stimulating the development of rural land rental markets.

Keywords: agricultural machinery services; land transfer; scale land operation; rice famers; rural China

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1. Introduction

Rice is one of the main foods of the whole world, and its planting area and output are basic guarantees for global food safety, especially for developing and transition economies. Scholars have conducted a lot of research on rice planting preferences and technology adoption [1–6]. For China as a rice consumer, specifically, Chinese scholars attach great importance to research fields related to rice production and management [7–10]. Rice production is an intensive production process, which requires a large number of laborers. For developing countries, where rural labor is constantly shifting to cities, in order to ensure rice production, it is necessary to figure out how to solve the shortage of agricultural labor [11]. The rural land household contract responsibility system (HCRS, which refers that the family responsibility system replaced the production team system and became the unit of production and income distribution [12]) is considered to be the most successful economic reform policy and institutional arrangement in China from the 20th century [13–15]. Since the implementation of HCRS, China has become the world's largest smallholder farming system [16]. However, small rice farmers are now facing a range of difficult challenges, such as, land fragmentation, farmland wastage, lack of agricultural workers. These

challenges continue to emerge, all of which harm agricultural production [17,18]. While, with the migration of young labor and the acceleration of rural aging, the area of rural land transfer is constantly increasing [19]. Against this backdrop, land transfer is becoming an important means to optimize the allocation of rural land resources [20–24]. Land transfer cannot only effectively solve the problem of scattered agricultural production land, but it can also increase the utilization rate of agricultural land [22,25–27]. According to statistics from the Ministry of Agriculture and Rural Affairs of China, from 2007 to 2017, China's land transfer area increased rapidly, from 64 million mu to 497 million mu, with an average annual growth rate of 23.67%. During the same period, the proportion of land transfer area in the total area of household contracted land increased from 5.20% to 36.97%—an average annual increase of 22.27% (see Figure 1). It can be seen that the incidence and area of land transfer in China continue to grow. Although the land transfer rate continues to increase, in fact, the overall situation of “big countries and small farmers” still exists [17].

Figure 1. Land transfer in China (2007–2017).

Agricultural mechanization is essential to the modernization of a country's agriculture. On the one hand, agricultural machinery can ease labor constraints and improve agricultural production efficiency. On the other hand, it can ensure food security and promote agricultural economic growth [28–30]. The adoption of agricultural machinery has brought tremendous changes to agricultural production. Over the past few years, the comprehensive mechanization level of China's crops has rapidly increased from 32.3% to 69%, with an average annual growth rate of 2.04%. During the same period, the total power of agricultural machinery increased from 525 million kilowatts to 1.0275 billion kilowatts, an average annual increase of 3.59%. Therefore, prior studies made great efforts to explore the impact of agricultural machinery on production [10,31–34]. In fact, the dissemination and expansion of new technologies is a serious challenge for small rice farmers, especially those in developing countries, who are generally older, with a low level of education and risk aversion [35–37]. However, agricultural machinery is a technology-intensive and capital-intensive investment, which places higher demands on farmers' capital and technology [31–33]. In order to popularize the use of agricultural machinery, the Chinese government has made great efforts through policy and financial instruments (e.g., subsidies for the purchase of agricultural machinery and mechanical training for farmers), especially to encourage the rise of agricultural machinery services [38]. An agricultural machinery service has many advantages. For example, it can increase the utilization rate of

agricultural machinery, and it can also provide convenience for farmers to use agricultural machinery [39,40].

Furthermore, previous studies mainly focused on agricultural machinery. Relevant studies have shown that agricultural machinery has played an active role in reducing agricultural production costs and reducing the uncertainty of new technologies [36,41–44]. For example, Disney and Elbashir (1984) studied the economic impact of agricultural machinery in Sudan and found that agricultural machinery increased agricultural productivity [42]. Recently, Paudel, et al. (2019) studied rice growing in the mountains of Nepal and found that using agricultural machinery increased rice productivity by 27% [5]. In addition, Qing, et al. (2019) used the data from 560 households in Northeast and North China; they found mechanization services improve farm productivity through substituting labor, while they may generate a less positive impact on farms without their owned equipment [10]. Besides, Wang, et al. (2016) used panel data from China, and figured out that agricultural machinery helps to increase agricultural productivity [45].

Overall, the existing studies have built a solid foundation for understanding the farmers' behavior of land transfer and the adoption of agricultural machinery service. However, there is still a research gap in agricultural machinery services. Even more, there is little literature to analyze regarding whether the use of agricultural machinery services can enable farmers to transfer more land. Thus, the primary goal of this study is to explore the impact of the adoption of agricultural machinery services on the land transfer behavior of rice households. Therefore, the marginal contributions of this paper are as follows: (1) a systematic study of the correlation between agricultural machinery services and land transfer of farmers can analyze how to coordinate technical elements and land elements to achieve optimal rice planting efficiency; (2) with filed survey data from rural areas in China, this study probes the relationship between machinery services and land transfer of rice farmers; (3) based on the empirical analysis, this study can assess the synergy of existing policies and provide empirical evidence for policy optimization.

The remainder of this study proceeds as follows. The next section displays the research framework of the relationship between agricultural machinery services and land transfer-in behavior of rice farmers. Section 3 introduces the source of research data, the descriptive analysis of variables, and the methodology selection. The empirical results of the model are presented in Section 4, and Section 5 provides a discussion of the results. Section 6 summarizes our main findings and discusses policy implications.

2. Research Framework

The theory of induced institutional innovation was proposed by Ruttan and Hayami in 1970 [46]. The core idea of the theory is that the relative scarcity of factor endowments promotes technological progress to save scarce factors. Therefore, when there is a shortage of labor in agricultural production, it will promote the development of mechanical technology. As we all know, the core and basic elements of agricultural production are land, labor, capital and technology. For developing countries that lack labor, especially China, the contribution of agricultural machinery services is mainly reflected in the relaxation of constraints on labor, capital and technological endowments in agricultural production [47–49]. The emergence of agricultural machinery services has changed the factor input and management modes of traditional agricultural production [9,28,50].

Firstly, agricultural machinery services can alleviate a shortage of agricultural labor [6,34,51]. The comparative advantage of non-agricultural employment has attracted a large number of young rural laborers, resulting in a shortage of agricultural labor [21,52,53]. When the supply of agricultural machinery services is sufficient and the market is perfect, farmers can alleviate labor pressure by purchasing agricultural machinery services in each link of the agricultural production process (such as mechanical tillage, mechanical sowing, unified control, mechanical collection, etc.) [47,52,54]. Secondly, agricultural machinery services can alleviate the financial pressure of agricultural production. Small-scale, decentralized operations and land division not only make it difficult for most farmers to invest in

agricultural machinery independently, but also limit the use of machinery technology [55]. In addition, agricultural machinery assets have strong specificity. If farmers buy all the agricultural machinery they need, then the high amount of funds will increase the economic burden of farmers [32,36]. Small farmers, however, can benefit from the use of machinery services through low-cost leasing [56,57]. In this way, agricultural machinery services could relieve the economic constraints brought by scale operation, thereby facilitating farmers' transfer-in land. Thirdly, agricultural machinery services can relieve the technical pressure of agricultural production. Specialized agricultural technologies (such as soil deep plowing, harvesting, soil measurement, fertilization formula, and so on) have been adopted for specialized agricultural machinery [37,58]. Agricultural machinery services can act as transmitters of agricultural technology, applying new agricultural science and technology to agricultural production, so that farmers can easily obtain and use new agricultural new knowledge [55]. As such, the adoption of agricultural machinery services can reduce the technical limitations of farmers' agricultural production so as to promote farmers' transfer to land and expand the scale of land management.

In summary, on the basis of the above theoretical analysis, with the development of China's agricultural machinery and land transfer market as the background, this study aims to provide empirical evidence for the following issues:

- (i) How do agricultural machinery services affect rice farmers' decisions on land transfer-in?
- (ii) Will the adoption of agricultural machinery services encourage rice farmers to transfer-in more land?
- (iii) How do other items (e.g., characteristics of the householder, the household, and the location) affect rice farmers' land transfer-in behavior?

3. Data and Method

3.1. Data Source

Since ancient times, Sichuan Province has been a major agricultural province in China. It is located in the Southwest of China. The rural population of Sichuan is about 57.63 million, which accounts for 63.33% of the total population. Sichuan's main crops include rice, wheat, corn, soybeans and tubers. The sown area of rice is 1.87 million hectares, accounting for about 30% of the total sown area of Sichuan's crops. As an important area for rice cultivation of China, during the past few decades, the yield of Sichuan rice increased from 319.2 kg/mu in 1978 to 524 kg/mu in 2019, and the yield increased by 64.16% (The related data comes from Sichuan Statistical Yearbook 2020 of the Sichuan Provincial Bureau of Statistics). As such, Sichuan province was selected as the research area.

The data used in this paper to examine the linkages between agricultural machinery services and land transfer were collected in a household survey of rice farmers by the authors and their research group from July to October in 2020. The fieldwork team conducted the data collection effort in Sichuan Province of China. This survey used questionnaire-based face-to-face interviews of rural households, involving questions on land use, agricultural machinery services status, family production, and other contents. As far as the specific sampling method was concerned, this study adopted an equal probability of selection within the stratum to generate samples [17,59].

Based on studies by Huang et al. (2020), Cao et al. (2018), Luo et al. (2017), and Ma et al. (2016) [17,59–61], a multistage sampling procedure was used for the selection of observation units. Firstly, 11 city-level districts were purposely selected based on the province intensity of rice production. These include 11 cities, i.e., Chengdu (the capital city of Sichuan), Deyang, Mianyang, Meishan, Suining, Ziyang, Luzhou, Neijiang, Dazhou, Nanchong, and Guang'an. In the second stage, 4 towns were randomly selected from each city using the information provided by local agricultural bureaus. Third, 2 villages were randomly selected from each sample township according to their level and location of social and economic development. Finally, 10 rural households were selected randomly from each village by using the village roster and a random number table. Through the above process, questionnaires were obtained from 880 households. After logical screening,

a total of 810 valid questionnaires were obtained after eliminating invalid samples, with an effective rate of 92.05%.

3.2. Method Selection

3.2.1. Definition and Data Description of the Model Variable

(1) Dependent variables

The dependent variable in this paper was the behavior of land transfer-in of farmers, which had two sub-dependent variables: one was the incidence of farmers' land transfer, which was a binary dummy variable; that is, the value of 1 was assigned to farmers who had transferred-in the land, and vice versa. The second was the area of farmers' land transfer-in, which was a continuous variable. We used the actual land transfer-in area of farmers to characterize this variable.

(2) Independent variables

The independent variable in this paper consisted of two categories. The first category was the core independent variable, which was agricultural machinery services, mainly referring to the number of agricultural machinery services purchased by farmers. The second category was the other control variables. We drew on the existing literature on land transfer, agricultural machinery adoption, and rural household behavior to select other exogenous explanatory variables [20,62–66]. As presented in Table 1, these variables included the characteristics of personal level, household level, and geographic location level.

Table 1. Variables and descriptive statistics.

Variables	Variable Specific Definition	Means	SD
Land transfer-in incidence	Whether farmers have transfer-in land (0 = no; 1 = yes)	0.928	0.258
Land transfer-in area	The area of farmers transfer-in land (μ ^a)	305.63	437.52
Machinery services	The quantity of agricultural machinery services purchased in agricultural production links	2.006	2.022
Head age	Household head's age (year)	49.12	10.28
Head education	The education level of household head (1 = if household head has a high school diploma or above; 0 = otherwise)	0.386	0.487
Head gender	The gender of household head (0 = female; 1 = male)	0.852	0.355
Agri-certificates	Whether farmers have agricultural certificates (0 = no; 1 = yes)	0.623	0.485
Household size	The total number of people in the household	4.680	1.636
Farm labor	The number of people engaged in agriculture	2.664	1.102
Off-farm labor	The number of family off-farm members	1.210	0.986
Subsidy	Whether farmers have land scale management subsidy (0 = no; 1 = yes)	0.249	0.433
Plain	Whether the majority of the land is located in a flat area (0 = no; 1 = yes)	0.473	0.500
Distance	Distance between household and the nearest business center (Km)	19.779	13.473

Note: ^a 1 μ = 667 m² or 0.067 ha.

Regarding personal characteristics of the household head, previous studies in developing countries have found positive effects of education and training on farmers' decisions to transfer-in land [63,66,67]. As mentioned by Schultz (1981) [68], knowledge is an important issue for human capital, which increases people's abilities to recognize, judge and respond to new things. Thus, we expected that both education and training have a positive impact on land transfer behavior. However, prior studies show that the probability of the area transferring-in land decreases when a household's age increases (Xu, et al. (2020) and Huang, et al. (2020)). Compared with young adults, older farmers are less likely to transfer-in land due to unfavorable health conditions. A study by Su, et al. (2018) reported that male-head households are more likely to transfer-in land, and we expected a similar influence of the gender variable on the likelihood of land transfer behaviors of a household. This is consistent with Mullan, et al. (2011) and Abebaw and Haile (2013), who found that a larger number of adults and farm-laborers in the household contributes to a higher probability of land transfer-in. Meanwhile, research by Xu (2020) reported that off-farm

employment has a negative impact on the probability of land transfer-in behavior, and we expect that this variable exerts a negative effect on land transfer-in behavior. With regards to subsidies, previous studies have shown that subsidies of scale management exert positive impacts on the probability of land transfer-in [69]. Moreover, longer distances to market are likely to increase transaction costs by farmers, and thus lead to a lower probability of the adoption of machinery services and participation in land transfer [67]. We also expect that terrain has a negative impact on agricultural machinery services and land transfer, because the higher the altitude, the more difficult it is to utilize agricultural machinery. Finally, the definition and assignment of all variables are shown in Table 1.

3.2.2. Model Construction

In this paper, probit and tobit were used to explore the impact of agricultural services on the decision making of farmers' land transfer behavior. That behavior includes two parts, i.e., the farmers' land transfer-in incidence and the land transfer-in area. This research intends to analyze the impact on the incidence of farmers' land transfer-in with the probit model. In addition, this study means to use tobit regression model to figure out the impact on the farmers' land transfer-in area. Thus, the basic formulas of econometric model constructed are as follow:

$$Transfer_i = \beta_0 + \beta_1 Agriserv_i + \beta_i X_i + \varepsilon_i \quad (1)$$

$$Area_i = \beta_0^* + \beta_1^* Agriserv_i + \beta_i^* X_i + \varepsilon_i^* \quad (2)$$

where the subscripts of, respectively, represent householder. *Transfer* is a dummy variable in which a value of 1 represents that the farmer has land transfer-in and a value of 0 represents otherwise. *Area* is a continuous variable which represents the area of a farmer's transfer-in. *Agriserv* is the core independent variable of this study model (the quantity of agricultural machinery services purchased in the rice production links by the farmer). X_i refers the explanatory variables that represent household, farm-level and location-level characteristics (e.g., age, gender, education, and so on) that are expected to affected land transfer-in behavior of rice farmers. Both β_0 and β_0^* are constant terms. $\beta_1, \beta_1^*, \beta_i^*$ and β_i^* are estimated parameters for the related variables. ε_i and ε_i^* represent the residual of the models. While, there may be a causal relationship between agricultural machinery service and land transfer-in behavior of farmers, and the core independent variable of this study may be endogenous. Thus, referring the study of Xu et al., Huang et al., Deng et al. [17,18,20], this research uses the appropriate instrumental variables in the model estimation. The study selected the average number of the quantity of agricultural machinery services purchased by farmers in the same township except the surveyed households as the instrument variable. That is, $IV_{Agriserv} = (Agriserv_1 + Agriserv_2 + \dots + Agriserv_n)/n$. As such, to ensure robust results, IV-Probit was used to estimate the impact on the incidence of farmers' land transfer-in, and the IV-Tobit model was used to examine the impact on the area of farmers' land transfer-in. The model formula are as follows:

$$Transfer_i = \beta_0 + \beta_1 Agriserv_i + \beta_i X_i + \varepsilon_i \quad (3)$$

$$Area_i = \beta_0^* + \beta_1^* Agriserv_i + \beta_i^* X_i + \varepsilon_i^* \quad (4)$$

The variables in Equations (3) and (4) are similar to those in Equations (1) and (2), and the entire process of this research was conducted via Stata 16.

4. Results

4.1. Descriptive Statistical Analysis Result

The meanings and descriptive statistics of the main variables used in this study are shown in Table 1. As shown in Table 1, in terms of the dependent variables, 92.8% of the farmers have the behavior of land transfer-in, and the average land transfer-in scale is 305.6 mu. In terms of core independent variables, farmers generally purchase

agricultural machinery services in ten links of rice production (agricultural machinery services in rice production mainly include rotary tillage, sowing, harvesting, irrigation, dosing, fertilization, weeding, drying, hulling, etc.). In terms of control variables, the average age of the household head was 49 years old, and 38.6% of the household heads had high school diplomas or above. Moreover, 62.3% of the respondents had agriculture-related certificates (for instance, new professional farmers, agricultural technicians, agricultural professional managers, etc.). For family level, the total family scale was 4.68. The average household had 2.67 agricultural labor forces and 1.21 off-farm labor force. In all, 24.9% of the households have the subsidy of land scale management. Additionally, almost 47.3% of the farmers' land is mainly in flat areas, and the average distance to the nearest business center was 19.779 km.

4.2. Multi-Collinearity Diagnosis

Before conducting our empirical analysis, it was considered that there may be some internal correlation among the measurement variables of the land transfer [70,71]. For continuous variables, the bivariate correlation matrix and variance inflation factor (VIF) were applied to identify and eliminate the collinear variable [72]. Thus, we carried out a multicollinearity test for each variable. Generally speaking, when $VIF = 1$, it can be considered that there is no collinearity among explanatory variables; when $VIF > 3$, it can be considered that there is a certain degree of collinearity among the explanatory variables; and when $VIF > 10$, highly collinearity among explanatory variables can be considered [73]. The diagnostic results with "land transfer-in scale" as the explained variable are shown in Table 2. Based on all test results, the degree of collinearity among explanatory variables is within a reasonable range, and there is no significant collinearity.

Table 2. Results of multicollinearity diagnostic.

Dependent Variable	Independent Variables	Multi-Collinearity Diagnosis	
		VIF Value	Expansion Factor
Land transfer-in area	Machinery services	1.15	0.871
	Head age	1.40	0.712
	Head education	1.29	0.773
	Head gender	1.04	0.963
	Agri-certificates	1.24	0.805
	Family scale	1.32	0.756
	Farm labor	1.31	0.764
	Off-farm labor	1.27	0.786
	Subsidy	1.16	0.862
	Plain	1.49	0.671
	Distance	1.33	0.751
	Mean VIF	1.27	

4.3. Econometric Model Results

Tables 3 and 4 present the empirical estimates. In Tables 3 and 4, the dependent variables of all models are continuous variables (land transfer-in area). Then, as in the studies of Deng, et al. (2020) and Huang, et al. (2020), this study used a causal identification strategy that gradually added explanatory variables. Even more specifically, model 1 to model 6 show the probit and iv-probit models for the incidence of farmers' land transfer-in. Among them, probit models were used in model 1 to model 3. Model 1 only shows core variable (agricultural machinery services) and model 2 gives the result, including core and controlled variables in Table 1. Model 3 reports the margin effects of model 2. In addition, iv-probit was adopted in model 4 to model 6, and margin effects of variables in model 5 were reported in model 6. Similarly, in Table 4, model 7 to model 12 display tobit models for the area of farmers' land transfer-in. Models 7 to 9 report the estimation results without an instrumental variable. Models 10 to 12 show the estimated results when instrumental

variables are used. Additionally, a marginal effect (i.e., Model 12) was calculated based on Model 11 to quantify the relationship. As the test statistics results of Endogenous Wald χ^2 , shown in Tables 3 and 4 ($p < 0.01$), demonstrate, the core variable (agricultural machinery services) is an endogenous variable. Thus, iv-probit and iv-tobit models were suitable for estimating the results of this research.

4.3.1. Impacts of Machinery Services on Land Transfer-In Incidence

Table 3 shows the probit model's estimation results of households' land transfer-in incidences. According to the results displayed in Table 3, machinery services were significantly positive ($p < 0.01$) for nearly all models (except the model 6, whose $p < 0.1$), which indicates that the impact of machinery services on land transfer-in incidence was positive. The pertaining coefficients were positive, which is in line with theoretical expectations. More specifically, as shown in the marginal effects estimates (Model 6 of Table 3), compared with other farmers, those who adopted machinery services in the rice production are 2.4% more likely to transfer-in land. Thus, there is a positive impact of machinery services on land transfer-in incidence; that is, the adoption of machinery services of farmers can help increase the incidence of land transfer-in.

Additionally, in Model 6 of Table 3, the coefficients of household head age, agri-certificates, family scale, farm labor, off-farm labor, subsidy, and distance are not significant, which indicates that the impact of those factors' impact on the households' land transfer-in incidences may not be distinct. While, the variables (i.e., head's education, head's gender, and plain) have significantly positive impact on farmers' enthusiasm for land transfer-in.

Table 3. The impact of agricultural machinery services on farmers' land transfer-in incidence.

Variables	Probit Models for Land Transfer-in Incidence			IV-Probit Models for Land Transfer-in Incidence		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Machinery services	0.302 *** (0.057)	0.277 *** (0.066)	0.031 *** (0.007)	0.551 *** (0.094)	0.446 *** (0.085)	0.024 * (0.013)
Head age		−0.002 (0.009)	−0.000 (0.001)		−0.002 (0.008)	0.000 (0.001)
Head education		0.376 * (0.204)	0.042 * (0.022)		0.331 * (0.194)	0.040 * (0.023)
Head gender		0.420 ** (0.193)	0.047 ** (0.022)		0.391 ** (0.192)	0.049 ** (0.023)
Agri-certificates		0.182 (0.161)	0.020 (0.018)		0.085 (0.165)	0.020 (0.019)
Family scale		0.045 (0.063)	0.005 (0.007)		0.053 (0.044)	0.007 (0.005)
Farm labor		0.135 (0.083)	0.015 (0.009)		0.112 (0.079)	0.014 (0.009)
Off-farm labor		−0.107 (0.083)	−0.012 (0.009)		−0.141 * (0.082)	−0.016 (0.010)
Subsidy		0.242 (0.173)	0.027 (0.019)		0.267 (0.170)	0.025 (0.020)
Plain		0.762 *** (0.221)	0.084 *** (0.025)		0.461 * (0.244)	0.055 ** (0.025)
Distance		−0.030 (0.107)	−0.003 (0.012)		−0.057 (0.113)	−0.008 (0.014)
Constant	1.063 *** (0.090)	−0.046 (0.679)		0.628 *** (0.148)	−0.170 (0.624)	−0.170 (0.624)
Instrumental variables	No	No	No	Yes	Yes	Yes
Wald χ^2	28.02 ***	68.64 ***	68.64 ***	34.73 ***	72.16 ***	72.16 ***
Endogenous Wald χ^2	−	−	−	14.86 ***	5.58 ***	5.58 **
Obs.	810	810	810	810	810	810

Note: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The impact of agricultural machinery services on farmers' land transfer-in area.

Variables	Tobit Models for Land Transfer-In Area			IV-Tobit Models for Land Transfer-In Area		
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Machinery services	0.328 *** (0.027)	0.208 *** (0.026)	0.198 *** (0.024)	0.857 *** (0.074)	0.536 *** (0.078)	0.134 * (0.073)
Head age		−0.015 ** (0.007)	−0.014 ** (0.007)		−0.016 ** (0.008)	−0.011 * (0.007)
Head education		0.575 *** (0.131)	0.548 *** (0.125)		0.544 *** (0.151)	0.511 *** (0.131)
Head gender		0.181 (0.174)	0.173 (0.166)		0.243 (0.185)	0.244 (0.162)
Agri-certificates		0.573 *** (0.136)	0.546 *** (0.130)		0.447 *** (0.151)	0.534 *** (0.132)
Family scale		0.035 (0.048)	0.034 (0.046)		0.053 (0.046)	0.056 (0.040)
Farm labor		0.052 (0.062)	0.049 (0.059)		0.036 (0.067)	0.040 (0.059)
Off-farm labor		−0.205 *** (0.067)	−0.195 *** (0.064)		−0.272 *** (0.075)	−0.247 *** (0.065)
Subsidies		0.282 * (0.152)	0.269 * (0.145)		0.343 ** (0.164)	0.227 (0.143)
Plain		0.938 *** (0.139)	0.894 *** (0.132)		0.600 *** (0.177)	0.551 *** (0.155)
Distance		−0.028 (0.092)	−0.026 (0.087)		−0.042 (0.104)	−0.056 (0.091)
Constant	3.887 *** (0.101)	3.480 *** (0.573)		2.775 *** (0.168)	3.055 *** (0.582)	
Instrumental variables	No	No	No	Yes	Yes	Yes
Wald χ^2	-	-	-	133.76 ***	321.93 ***	321.93 ***
Endogenous Wald χ^2	-	-	-	83.30 ***	22.69 ***	22.69 ***
Obs.	810	810	810	810	810	810

Note: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Impacts of Machinery Services on Land Transfer-In Scale

Table 3 displays the tobit models' estimation results of households' land transfer-in area. As the results showed in Table 4, in terms of the impact of machinery services on land transfer-in area of a household, an agricultural machinery services area is significantly positively correlated with a household's land transfer-in area, and the results are robust. The pertaining coefficients were positive, which is in line with theoretical expectations. More specifically, with every 1% increase in machinery service, the average area that land transfer-in area of household increases by 13.4% (model 12).

In addition, the coefficients of head of household age, their education, agri-certificates, off-farm labor, and plain are significant, which means those variables may promote or inhibit land transfer-in area of households. Particularly, head education, agri-certificates, and plain are significantly correlated with land transfer area of households. Head of household age and off-farm labor are significantly negatively related to land transfer-in area of households. However, variables such as head gender, family scale, family farm labor, and distance to market are not significant in the model, indicating the impact of those variables may be not distinct.

4.4. Estimated Results of Robustness Tests

Considering that the impact of agricultural machinery services on household's land transfer behavior may not be very robust, this study uses two robustness tests for the subsequent analysis. Firstly, referring to the study of [9,20], The cost of purchasing agricultural machinery services is used to replace the core independent variable. Secondly, the dependent variable of those models (land transfer-in area) is approximately regarded as continuous variables; thus, the iv-reg model was used to estimate the results. Even more specifically, all core independent variables in models of Table 5 have been replaced. Besides, model 15 and model 16 used iv-reg method to estimate instead of iv-probit. Similarly, model 19 and model 20 used iv-reg instead of iv-tobit. The results are presented in Table 5.

Table 5. Robustness test results.

Variables	Robustness Check Models for Farmers Land Transfer-in Incidence (Test I)				Robustness Check Models for Farmers Land Transfer-in Area (Test II)			
	Model 13	Model 14	Model 15	Model 16	Model17	Model 18	Model 19	Model 20
Machinery services	0.201 *** (0.035)	0.218 *** (0.046)	0.047 *** (0.008)	0.034 *** (0.011)	0.266 *** (0.026)	0.180 *** (0.024)	0.730 *** (0.067)	0.546 *** (0.084)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Instrumental variables	No	No	Yes	Yes	No	No	Yes	Yes
Wald χ^2 /F value	58.61 ***	71.71 ***	34.18 ***	74.02 ***	99.70 ***	303.27 ***	288.68 ***	120.10 ***
Obs.	810	810	810	810	810	810	810	810

Note: Rousted standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As shown in Table 5, it can be seen that, in terms of the impact of agricultural machinery services on land transfer-in incidence, whether this study replaced the core independent variable or replaced the measuring, the direction and significance of the correlations are all consistent with the previous estimate analysis results. The only difference lies in the correlation coefficients (corresponding to the robustness test I). To be specific, agricultural machinery services are significantly positively and robustly correlated with whether households have land transfer-in. Besides, whether we add the control variables or not, the results remain highly consistent.

Similarly, in term of the impact of agricultural machinery services on land transfer-in area, regardless of whether we replace the core variable or replace the method, the direction and significance of the conclusion are consistent with previous research. The difference merely lies in the correlation coefficients (corresponding to the robustness test II). Specifically, agricultural machinery services are significantly positively and robustly related to land transfer-in area. What is more, whether we add the control variables or not, the results of the correlations between machinery services and land transfer-in area are also in line with those of the previous study.

5. Discussion

With the field survey data of 810 rice households of Sichuan Province China in 2020, iv-probit and iv-tobit models were used to probe the impact of agricultural machinery services on the land transfer of rice householders. This study mainly has three contributing points which can make up for the shortcomings of existing research.

Firstly, in the exploration of agricultural mechanization on land transfer, this study mainly focused on the impact of agricultural machinery services on land transfer behavior of households. It is novel to pay attention to the machinery service, especially for farmers who normally lack labor, technology and funds in developing countries. Secondly, in addition to using the iv-probit and iv-tobit models to deal with possible endogenous problems of model settings, this study also further considers the strategies of the replacing core independent variables and replacing the estimation method to probe robustness tests on existing research results.

In this way, the effectiveness and robustness of the iv-probit and iv-tobit models are further verified. Thirdly, the samples of this study cover 810 householders in Sichuan province of China. Since Sichuan is not only a large rice production province but also a multi-terrain agricultural province, the empirical evidence of this study may provide a meaningful reference for agricultural mechanization development and moderate scale land management for some other provinces in China (e.g., Guizhou, Yunnan, Chongqing), and also other developing countries (e.g., Mongolia, Nepal, Pakistan).

There are three reasons why agricultural machinery services promote the land transfer behaviors of farmers: (i) Agricultural machinery services can improve technical efficiency [15,32]. As an important sign of modern agriculture, mechanization is conducive with promoting the technical efficiency of rice production [40]. (ii) Agricultural machinery services are beneficial for easing labor constraints [10]. With the development of economic levels and urbanization, a large number of the rural labor force is transferring to cities and towns, which makes the lack of rural labor force problematic, especially in busy farming periods [20,53]. For staple food crops such as rice, agricultural machinery can be used in multiple agricultural production links, including mechanized plowing, mechanized sowing, plant protection, mechanized harvesting, etc., to alleviate the pressure of rural labor shortages. (iii) Agricultural machinery services can save production costs [5,58]. On the one hand, due to the shortage of agricultural labor, agricultural labor wages continue to increase; agricultural machinery services can effectively relieve the financial pressure caused by employment [22]. On the other hand, there are differences in agricultural machinery used in each production link in agriculture. Farmers' purchase of agricultural machinery required by all links will seriously increase the burden of farmers' production and management [27,74]. Agricultural machinery services cannot only save a large number

of funds but also ease financial constraints faced by farmers on scale operations, thereby helping farmers to expand the area of land transfers.

Compared with previous studies' results and findings, this study has shown some similarities and differences. Firstly, we found machinery services have a significantly positive impact on the land transfer behavior of farmers, which is in the line with the findings from Yang, et al. (2013) and Weng and Xu (2019) [49,75]. However, unlike previous studies, we have found that agricultural machinery services are not only conducive to the incidence of farmers' land transfer-in, but also conducive to the increase of land transfer-in area. Secondly, some other control variables (such as head's age, head's education, agricultural certificates, plain, subsidy and off-farm labor) have a significantly different degree of effect on land transfer-in behavior. This is consistent with the research of Deng, et al. (2020), Huang, et al. (2020), Xu, et al. (2020), Gao, et al. (2020), and Rzaşa, et al. (2019). Last but not the least, the core independent variable setting of this study is different from the studies by Yang, et al. (2013), Liu, et al. (2017), and Carter and Yao (2002) [49,76,77], whereas in line with Huang, et al. (2020) and Xu, et al. (2020). This study strictly distinguishes the dependent variable, that is, land transfer-in behavior is divided into farmers' land transfer-in incidence and land transfer-in area. Considering the endogenous of variables, through the estimated strategies and robustness test strategies, the results showed that iv-probit and iv-tobit were more suitable for this study.

Additionally, there are some shortcomings in this study which could be addressed in future research. Among them are the following: (i) The impact of agricultural machinery services on land transfer-in behavior is a dynamic process. This study only used cross-sectional data to discuss this relationship. Panel data could be adopted in future studies to capture a better insight. (ii) This study only focused on agricultural machinery services. While, the adoption of agricultural machinery actually includes two aspects, that is, farmers use their own machinery or purchase machinery services. Further studies may also probe the impact of farmers' own machinery on land transfer-in behavior. (iii) Meanwhile, there are also two dimensions of land transfer, namely land transfer-in and land transfer-out. The impact of agricultural machinery services on land transfer-out could be explored in future research.

6. Conclusions and Implications

On the basis of the above analysis, the following three conclusions can be drawn:

- (1) Agricultural machinery services have had a significantly positive and robust impact on rural householders' land transfer-in behavior. However, there are some different impacts between the incidence and area of farmers' land transfer-in. When other conditions remain unchanged, for every 10% increase in machinery services rate, the rate in land transfer-in will increase by an average of 2.4%, while the area of land transfer-in will increase by an average of 13.4%.
- (2) Other control variables have different effects on land transfer-in behavior. For instance, head of household education, agricultural certificates, and whether the majority of land is in a flat area have significant impacts on farmers' land transfer-in incidence and area.

The study of this paper proves the importance of agricultural machinery services in promoting land transfer. According to the above findings, we can also derive some policy implications. First of all, agricultural machinery services play a vital role in land transfer. Hence, in order to make agricultural machinery services more common and reduce information asymmetry, the government needs to improve the informatization and standardization of agricultural machinery services, and establish a sharing platform for agricultural machinery services. In addition, we found that the plain has a clear positive effect on land transfer-in area. In other words, as land elevation increases, the possibility of farmers' land transfer-in will decrease. Therefore, the government should actively promote research and development of small and medium-sized agricultural machinery to further improve the scope of services to meet the service needs of different scales and regions. It is

also beneficial to reduce land abandonment in different terrain. Moreover, this study finds that the education and certificates of the household's head may be conducive to increasing the possibility of farmers' land transfer-in behavior. This suggests that the government should provide more agriculture-related training and provide more agricultural knowledge to farmers so as to cultivate a new type of professional farmer.

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