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Agricultural Social Services and Land Transfer: A Multidimensional Analysis of Impacts on Land Allocation

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Abstract: Land transfer is a crucial measure for optimizing cropland allocation and improving production efficiency, especially in resource-scarce countries. Drawing on a sample of 858 farmers from Sichuan Province, China, this study examines whether agricultural social services (ASSs) drive land transfer. Unlike previous research that focused on a single dimension, such as participation or scale, this paper examines land transfer behavior from three dimensions: participation, scale, and future transfer willingness. Using an endogenous switching regression model and a probit model, we analyze unique cross-sectional farm-level data collected from rural China. The results indicate that ASSs have a positive and significant impact on land transfer behavior: (1) ASS adoption increases the land transfer participation rate by 13.7%. (2) The transfer area increases by 74.34% due to ASSs. (3) The likelihood of future transfer increases by 4.2% with ASS adoption. These findings suggest that fostering a supportive environment for agricultural social services can enhance the land transfer market and contribute to sustainable modernization of the agricultural sector.

Keywords: agricultural social services; land transfer participation; transfer scale; future transfer willingness; endogenous switching model; rural China

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1. Introduction

1.1. Research Background

With rapid urbanization in China, large-scale migration of young rural labor to non-agricultural sectors has become a prominent socio-economic phenomenon. This trend has resulted in labor shortages in the agricultural sector, raising relevant policy issues, such as arable land abandonment [1], declining agricultural productivity, and threats to national food security [2]. Given China's large population and limited arable land, addressing land abandonment to ensure food security in the face of a shrinking agricultural labor force has become a pressing research topic. Market-oriented land transfer is considered an effective strategy to address these challenges [3]. Its core mechanism involves reallocating idle land from some farmers to others willing to cultivate it to improve land use efficiency [4]. Existing research has explored this issue extensively. At the macro-level, studies highlight the influence of factors such as economic development, political stability, social security systems, and the quality of the natural production environment on land transfer behavior. At the micro-level, however, a large body of research has focused on how individual

farmer characteristics, such as family structure, social networks, off-farm employment, and organizational forms like cooperatives, impact land transfer decisions [5–7]. Available evidence suggests that land transfer and large-scale land management face significant internal and external constraints, which intensify as the scale of land management grows. Challenges such as labor shortages, limited capital, and increasing agricultural production risks become more prominent with increasing farm operations [8–10]. These issues not only reduce farmers' productivity and motivation but also hinder land transfer and large-scale land management decisions. To ensure the efficient allocation of land resources and sustainable agricultural development, a systematic analysis of these challenges and the formulation of targeted policy measures are essential.

As modern agriculture continues to advance, agricultural socialized services (ASSs) have become relevant in agricultural production. Agricultural socialized services are bundled services that comprise agricultural input supply services (AMSs), agricultural credit services (ACSs), agricultural technical services (ATSs), and agricultural machinery services (AMAs). These services play a crucial role in modernizing agriculture to ensure food and nutritional security [11,12]. Additionally, ASSs help alleviate agricultural labor shortages and enhance overall production capacity [13,14]. Against this backdrop, understanding the impact of ASSs on farmers' land transfer decisions has become a critical area of interest for both researchers and policymakers. Specifically, key questions of interest include whether ASSs influence farmers' decisions to engage in land transfer, the scale of land transfer, and their willingness to transfer land in the future. While many studies have explored the factors affecting land transfer participation and scale, research on farmers' future land transfer intentions remains limited. Given the uncertainties inherent in the natural environment and agricultural activities, farmers' intentions for future land transfer are subject to considerable unpredictability. Therefore, systematically analyzing farmers' decision-making behavior in land transfer is crucial for improving land resource efficiency, promoting large-scale farming operations, and enhancing agricultural competitiveness. This study intends to investigate the impact of ASSs on land transfer decisions in rural China.

1.2. Theoretical Analysis

1.2.1. Farmer Behavior Theory

The theory of farmer behavior posits that farmers' objective of maximizing utility is driven by both external environments and individual characteristics [15]. In agricultural production, land transfer decisions constitute a critical decision farmers have to make among various options available. Agricultural socialized services (ASSs) significantly reshape farmers' production environments and cost–benefit structures by providing comprehensive support [16–18]—including technical guidance, agricultural input supply, and product marketing—thereby influencing their land transfer decisions. On the one hand, ASSs effectively reduce production costs. For instance, by offering high-quality agricultural inputs at lower prices and advanced technical services, farmers' expenditures on materials and services decrease [11,19,20]. This cost reduction incentivizes greater participation in land transfer markets and encourages expanded transfer scales. On the other hand, ASSs enhance farmers' expected returns by improving market access to cause an increase in product output prices to boost sales volumes, which enhances farmers' expected incomes to incentivize land transfer participation. Furthermore, ASSs influence land transfer decisions by mitigating farmers' risk perceptions. Farmers' yields are highly exposed to production and market risks. By mitigating these risks, ASSs increase farmers' expected returns from their production activities to foster land transfer participation.

1.2.2. Cost Theory

From a cost theory perspective, land transfers involve multiple expenses, comprising fixed (e.g., contract signing and land preparation fees) and variable costs (e.g., labor and agricultural inputs) [21]. Agricultural socialized services (ASSs) primarily influence land transfers by altering the structure and magnitude of these costs. First, ASSs help to reduce fixed costs associated with land transfers. ASSs, for example, provide intermediary services for land transfers by leveraging extensive land resource databases and professional contract drafting expertise. These services streamline preparatory work at lower costs, thereby lowering fixed expenses for farmers. Second, ASSs exert a more pronounced impact on variable costs. Mechanized farming services reduce reliance on labor, cutting labor costs, while bulk purchasing of agricultural inputs and precision fertilization/pesticide services lower material expenses [22,23]. The reduction in variable costs enhances post-transfer profitability, making farmers more willing to engage in land transfers and expand their scale. Finally, from a long-term cost–benefit perspective, ASSs foster economies of scale in land transfers by improving land use efficiency and agricultural productivity. As transfer scales reach optimal levels, per-unit production costs decline while output increases, creating a self-reinforcing cycle that further incentivizes land transfers. The analysis framework is depicted in Figure 1.

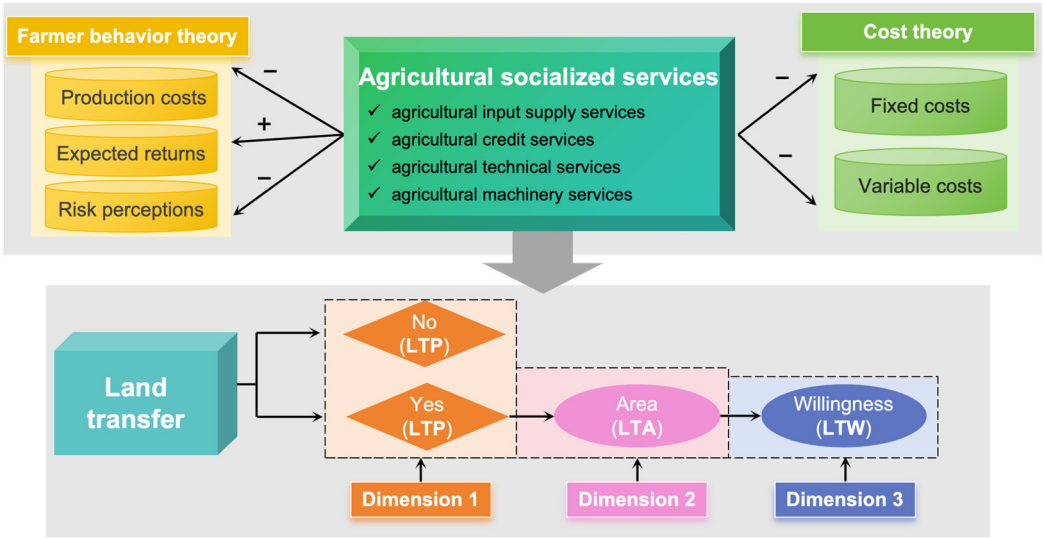


Figure 1. Analysis framework.

Accordingly, this study proposes the following research hypotheses:

H1. *ASS adoption positively impacts farmers' land transfer participation.*

H2. *ASS adoption positively influences farmers' land transfer area.*

H3. *ASS adoption positively affects farmers' intentions for future land transfer.*

This paper makes several contributions to the field: First, it develops a multidimensional framework to examine the mechanisms through which ASSs influence farmers' land transfer behavior across three dimensions: transfer participation, transfer scale, and future transfer willingness. Second, it applies endogenous switching models (endogenous switching regression model and endogenous switching probit model) to analyze the effects of ASSs on land transfer behavior from a micro-level perspective, addressing endogeneity issues found in prior studies. Third, using detailed data from 858 farmers in Sichuan Province, this study provides empirical evidence of the relationship between ASSs and land

transfer behavior, offering new insights into the role of ASSs in land markets. Finally, the findings have practical implications for policy, offering data-driven support for developing targeted measures to foster land transfer markets and modernize agriculture. By enriching the research on ASSs and its impact on land transfer, this paper provides both theoretical foundations and actionable guidance for achieving sustainable agricultural development and optimizing land resource allocation.

2. Materials and Methods

2.1. Data Description

This study is based on data collected through a random sampling survey of rice farmers in Sichuan Province between July and October 2020. A stratified random sampling method was employed to ensure the sample's representativeness and diversity. Initially, 11 major rice-producing cities in Sichuan Province were selected, including Chengdu, Deyang, Mianyang, Ziyang, Meishan, Suining, Neijiang, Nanchong, Dazhou, Guang'an, and Luzhou (Figure 2). Within each city, two county-level administrative districts were randomly chosen, followed by the selection of 2–3 towns per county. Finally, 10–20 rice-farming households from each town were interviewed through face-to-face questionnaires, resulting in a dataset of 858 valid samples. These samples encompass diverse geographical, economic, and social contexts, providing a robust empirical foundation for this study.

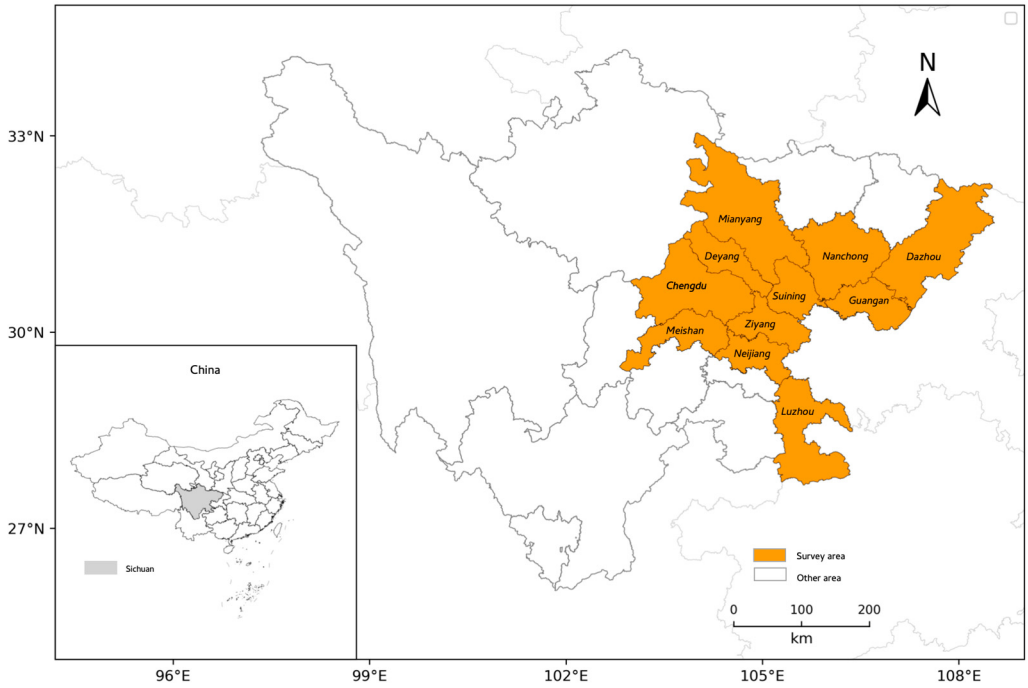


Figure 2. Study area.

2.1.1. Selection of Variables

Building upon previous studies [7,24–26], this paper systematically designs the selection of variables. The dependent variable, farmers' land transfer decisions, is analyzed across three dimensions: (1) land transfer participation (LTP), indicating whether farmers engaged in land transfer in 2019 (1 for participation, 0 for non-participation); (2) land transfer area (LTA), referring to the actual amount of land transferred in 2019 (measured in mu); and (3) future willingness to transfer land (LTW), reflecting farmers' attitudes toward future land transfer (1 for willing, 0 for unwilling).

The treatment variable in this study is the adoption of ASSs, represented by a binary variable (1 for adoption, 0 for non-adoption). To ensure the robustness and accuracy of

the model, a range of control variables is incorporated. These include characteristics of the household head (e.g., age, gender, education level), family and farm attributes (e.g., family size, farm type), location-specific factors (e.g., geographical location, soil quality), and regional dummy variables to account for heterogeneity across different areas.

Additionally, based on peer effects theory, which posits that individual behavior is influenced by the actions of others, the town-level adoption rate of ASSs is introduced as an instrumental variable (IV) to examine its potential impact on farmers' adoption decisions. This variable helps address selection bias and captures the diffusion of ASSs within communities, providing a more robust empirical foundation for the analysis. Through this systematic selection of variables, this study aims to comprehensively explore the mechanisms through which ASSs influence farmers' land transfer decisions.

2.1.2. Descriptive Statistical Analysis

Table 1 presents the variable definitions and their descriptive statistics. The dataset consists of 858 observations, capturing key aspects of farmers' land transfer behavior and ASS adoption. In 2019, 86.4% of farmers participated in land transfer, with an average transferred land area of 205.54 mu. Additionally, 80.1% of farmers expressed a willingness to transfer land in the future, indicating strong ongoing engagement in land transfer activities. ASS adoption is also high, at 84.3%, highlighting its significant role in supporting agricultural operations. Demographically, 85.2% of respondents are male, with an average age of 48.93 years and 8.783 years of formal education. Household size averages 4.653 members, and 1.186 family members work outside agriculture, reflecting the prevalence of off-farm employment. Farmers have extensive agricultural experience, averaging 16.85 years, and 77.3% own motor vehicles, suggesting relatively good access to transportation. Wi-Fi access has been available for an average of 6.477 years, indicating moderate digital connectivity. Geographically, farmers live an average of 3.822 km from the township center. Soil quality is rated as "good" by 55.5% of respondents, while 55.4% reside in hilly or mountainous areas, underscoring terrain-related challenges in land management. Overall, the data highlights high levels of land transfer participation and ASS adoption, alongside socio-economic and geographic factors that shape farmers' decisions and agricultural practices.

Table 1. Variable definition and descriptive statistics.

Variable	Definition	Mean.	St. Dev.	Min	Max
LTP	Whether farmer has transferred land in 2019. Yes = 1, no = 0	0.864	0.343	0	1
LTA	Area of land transferred (mu)	205.54	282.42	0.800	1440
LTW	Farmer's willingness to transfer in the future. Yes = 1, no = 0	0.801	0.400	0.588	7.273
ASS	Whether farmer adopt ASS. Yes = 1, no = 0	0.843	0.364	0	1
Gender	Male = 1, female = 0	0.852	0.355	0	1
Age	Age of respondent (years)	48.93	10.27	19	78
Age squre	Natural log of age squared	7.733	0.451	5.889	8.713
Education	Respondents' years of education (years)	8.783	3.433	0	16
Family size	Total number of respondents' households	4.653	1.651	1	63
Off-farm	Number of family members working outside the home (person)	1.186	0.978	1	16
Agr- experience	The respondents have worked in agriculture for years (years)	16.85	13.06	0	6
Own vehicles	Ownership of motor vehicles. Owned = 1, not owned = 0	0.773	0.419	0	1
Wi-Fi	Years with home Wi-Fi (for the respondent)	6.477	4.410	0	22
Distance	Distance from respondent's residence to township center (km)	3.822	2.816	0	1
Soil quality	Good = 1, normal = 0	0.555	0.497	0.0488	2.708
Terrain	Whether farmer lives in hilly or mountainous area. Yes = 1, no = 0	0.554	0.497	0	1
Obs.	858				

2.1.3. Mean Difference

Table 2 presents a detailed comparison of the average differences between farmers who have adopted ASS and those who have not. An analysis of the mean differences reveals that there are statistically significant disparities between the two groups of farmers on most

variables, indicating that there are indeed systematic differences between those who have adopted the services and those who have not. Specifically, the adoption group exhibits significantly higher rates in key indicators such as LTP, LTA, and LTW compared to the non-adoption group. These differences preliminarily uncover the potential pivotal role that ASSs may play in farmers' land transfer decisions. The LTA is higher for non-participants. However, at higher levels, participants (ASS) tend to transfer more land (see Figure 3).

Table 2. Mean difference between the two groups.

Variable	ASS Adopter	ASS Non-Adopters	Mean.	St. Dev.	t-Value
LTP	0.931	0.504	0.427 ***	0.029	14.9
LTA	245.049	17.173	227.875 ***	25.303	9
LTW	0.876	0.4	0.476 ***	0.034	14.05
Gender	0.862	0.8	0.062 *	0.034	1.85
Age	48.17	53.015	−4.845 ***	0.95	−5.1
Age squre	7.704	7.886	−0.182 ***	0.419	−4.35
Education	9.145	6.841	2.304 ***	0.313	7.4
Family size	4.606	4.904	−0.298 *	0.154	−1.95
Off-farm	1.137	1.452	−0.315 ***	0.091	−3.45
Agr-experience	15.506	24.074	−8.568 ***	1.19	−7.2
Own vehicles	3.766	4.12	−0.353	0.264	−1.35
Wi-Fi	6.857	4.437	−2.421 ***		
Distance	0.583	0.408	0.175 ***	0.046	3.8
Soil quality	0.812	0.563	0.249 ***	0.038	6.5
Terrain	0.499	0.845	−0.345 ***	0.045	−7.65
Obs.	723	135			

Note: (1) * and *** sub-tables represent estimates that are significant at the 10% and 1% levels.

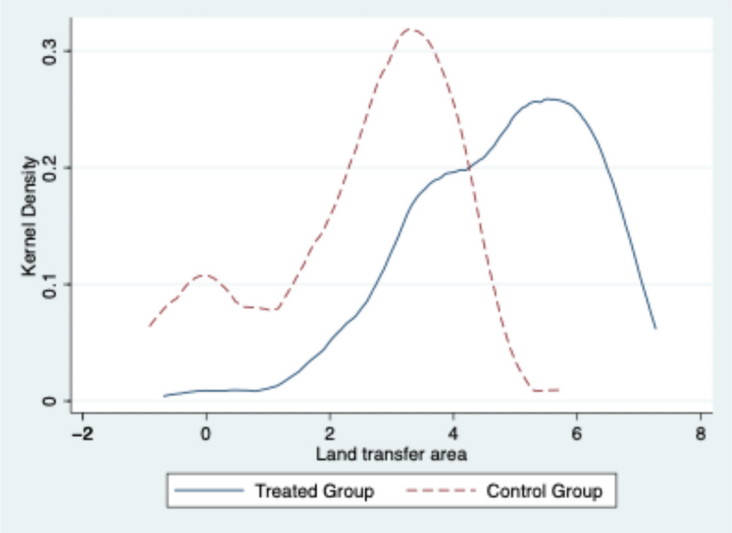


Figure 3. Kernel density of land transfer area.

Upon further examination, it is observed that the group of farmers who have adopted the services tends to be relatively younger, with a longer duration of education, a lower proportion of laborers working outside their hometowns, a shorter history of engagement in agricultural production, superior soil quality, a higher proportion of motor vehicle ownership, and a greater distribution of land outside of hilly and mountainous areas. These characteristics suggest that the adoption of ASSs may be closely associated with factors such as the individual attributes, family conditions, production environments, and geographical locations of the farmers. Given this, this study argues that using an endogenous switching model is crucial for reducing potential selection biases from both measurable and unmeasurable factors.

2.2. Model Construction

This study investigates the impacts of the adoption of ASSs on farmers' land transfer decisions. Decisions regarding the adoption of ASSs are not random. Rather these decisions are based on the expected benefits, which are driven by a myriad of factors including household resource endowments, making those ASS adopters systematically different from those who do not adopt. As shown in Table 2, there exist significant differences in key characteristics between service adopters (treatment group) and non-adopters (control group). This indicates that ignoring endogenous selection bias in quantitative analyses may lead to inaccurate estimates of the impact of ASS adoption on land transfer behavior [27,28]. Although methods such as the Propensity Score Matching (PSM) and instrumental variable (IV) approaches are commonly used to address selection bias, the endogenous switching model is more effective in accounting for biases from both observable and unobservable factors. Neglecting unobservable factors can result in biased estimates. To address this, this study employs the endogenous switching regression (ESR) and endogenous switching probit models. These models allow for a more accurate assessment of the causal relationship between ASS adoption and farmers' land transfer decisions while controlling for unobservable factors that influence the decision to adopt services.

2.2.1. Endogenous Transformation Model

The endogenous switching model is divided into two main stages, aimed at deeply analyzing the decision-making process of adopting ASSs and its impact on land transfer choices. The first stage examines decisions to adopt ASSs. We express the expected benefits of service adoption by farmer (i) as ASS_{ia}, and the expected returns of not adopting the services as ASS_{in}, and the expected net return as $ASS_i^* = ASS_{ia} - ASS_{in}$. Therefore, farmers decide to adopt the service only if $ASS_i^* > 0$. Considering the subjective nature of expected net returns and their unobservable character, this paper uses an unobserved latent variable to represent them:

$$ASS_i^* = \gamma Z_i + \mu_i, \text{with } ASS_i = \begin{cases} 1, & if \ \ ASS_i > 0 \\ 0, & otherwise \end{cases} \quad (1)$$

where ASS_i represents a binary variable, 1 indicates adoption of services, and 0 indicates non-adoption. Z_i is a vector of explanatory variables, including household head characteristics and family traits. γ is the parameter vector to be estimated, and (μ_i) is a random error term.

The second phase entails estimating the impact of ASS adoption on the choice of land transfer, namely the effects on the decision to transfer land, the area of land transferred, and the future intention to transfer land. Under the condition where services can be opted for, two categorical equations represent the land transfer decisions with and without the adoption of services [29,30]. The specific model is as follows:

(1) Impact on land transfer participation

$$\begin{cases} LTP_{1i}^* = \alpha_{11} X_{1i}' + \varepsilon_{11i}, \ LTP_{1i} = \begin{cases} 1, \ LTP_{1i}^* > 0 \\ 0, \ LTP_{1i}^* < 0 \end{cases} & for \ ASS_i = 1 \\ LTP_{0i}^* = \alpha_{10} X_{0i}' + \varepsilon_{10i}, \ LTP_{0i} = \begin{cases} 1, \ LTP_{0i}^* > 0 \\ 0, \ LTP_{0i}^* < 0 \end{cases} & for \ ASS_i = 0 \end{cases} \quad (2)$$

(2) Impact on the scale of land transfers

$$\begin{cases} LTA_{1i} = \alpha_{21} X'_{1i} + \varepsilon_{21i} \quad if \quad ASS_i = 1 \\ LTA_{0i} = \alpha_{20} X'_{0i} + \varepsilon_{20i} \quad if \quad ASS_i = 0) \end{cases} \tag{3}$$

(3) Impact on future intention to transfer land

$$\begin{cases} LTW^*_{1i} = \alpha_{31} X'_{1i} + \varepsilon_{31i},\ LTW_{1i} = \begin{cases} 1,\ LTW^*_{1i} > 0 \\ \qquad\qquad for\ ASS_i = 1 \\ 0,\ LTW^*_{1i} < 0 \end{cases} \\ LTW^*_{0i} = \alpha_{30} X'_{0i} + \varepsilon_{31i},\ LTW_{0i} = \begin{cases} 1,\ LTW^*_{0i} > 0 \\ \qquad\qquad for\ ASS_i = 0 \\ 0,\ LTW^*_{0i} < 0 \end{cases} \end{cases} \tag{4}$$

In the above equations, LTP^*_{1i} and LTP^*_{0i}, LTA_{1i} and LTA_{0i}, and LTW_{1i} and LTW_{0i} represent the participation in land transfer, the scale of land transfer, and the willingness to transfer land in the future for service adopters and non-adopters, respectively. X denotes a vector of explanatory variables, including household head, family, and demographic characteristics. α is the vector of estimated parameters, and ε is the random error term. Following the framework of the endogenous switching model, the endogenous switching probit model Equations (1) and (2), (1) and (3), and the endogenous switching regression model Equations (1) and (4) are estimated using the full information maximum likelihood (FIML) method.

To accurately identify the endogenous switching model, at least one instrumental variable is required that influences service adoption but does not directly affect the outcome equation. Based on the theory of peer effects [31], individual behavior is significantly influenced by the actions of peers. Studies within this framework [32] show that decision-making is shaped by the behaviors of one's peers. Therefore, this study uses the village-level rate of ASS as an instrumental variable to capture the influence of peer effects on farmers' service adoption.

The Pearson correlation test reveals a significant positive relationship between the village-level rate of ASS and the adoption of services by the surveyed farmers. However, no statistically significant correlation is found between this variable and farmers' land transfer choices, including participation, scale, and future willingness. This result confirms that the town-level usage rate meets the exclusion restriction condition for instrumental variables. It is related to service adoption but not directly to land transfer outcomes. By using this instrumental variable, this study effectively controls for endogeneity, providing more accurate estimates of the impact of agricultural socialized service adoption on land transfer behavior.

2.2.2. Average Treatment Effect Estimates

Following the estimation of the two stages in the endogenous switching model, the variable coefficients are used to examine the impact of agricultural socialized service adoption on farmers' land transfer decisions. Using the analytical framework of Lokshin and Sajaia [29], this study calculates the Average Treatment Effect on the Treated (ATT), which represents the difference in land transfer behavior between service adopters (treatment group) and their counterfactual scenario.

$$ATT_{LTA} = E[LTA_{1i}|ASS = 1] - E[LTA_{0i}|ASS = 1] = X_i(\gamma_{1i} - \gamma_{0i}) + \lambda_1(\sigma_{1\mu} - \sigma_{0\mu}) \tag{5}$$

$$ATT_{LTP} = \frac{1}{N_1}\sum_{i=1}^{N_1}[P_r(LTP_1 = 1|ASS = 1, X = x) - P_r(LTP_0 = 1|ASS = 1, X = x)] = \frac{\Phi_2(X_1\alpha_1, \gamma Z, \rho_1) - \Phi_2(X_0\alpha_0, \gamma Z, \rho_0)}{F(\gamma Z)} \quad (6)$$

$$ATT_{LTW} = \frac{1}{N_1}\sum_{i=1}^{N_1}[P_r(LTW_1 = 1|ASS = 1, X = x) - P_r(LTW_0 = 1|ASS = 1, X = x)] = \frac{\Phi_2(X_1\alpha_1, \gamma Z, \rho_1) - \Phi_2(X_0\alpha_0, \gamma Z, \rho_0)}{F(\gamma Z)} \quad (7)$$

where Φ_2 represents the cumulative distribution function of a bivariate normal distribution, while $F(\gamma Z)$ denotes the cumulative distribution function of a univariate normal distribution. N_1 is the number of treatment groups ($LTP = 1$ and $LTW = 1$), and $P_r(LTP_1 = 1|I = 1, X = x)$ and $P_r(LTW_1 = 1|I = 1, X = x)$ indicate the probabilities that a service adopter participates in land transfer and is willing to continue transferring land in the future, respectively. Conversely, $P_r(LTP_0 = 1|I = 1, X = x)$ and $P_r(LTW_0 = 1|I = 1, X = x)$ denote the probability that in the counterfactual scenario, farmers who adopt the service do not switch to land and the probability that they do not want to switch to land in the future, respectively.

This calculation compares farmers who adopt ASSs to those who do not to uncover the actual effects of ASS adoption on land transfer decisions. Using statistical models, this study evaluates changes in the likelihood and extent of land transfer associated with service adoption, along with the quantitative implications of such changes. The analysis covers participation, transfer scale, and future intentions, offering a comprehensive view of how ASS influence land transfer. This framework helps identify and measure the role of these services in improving land use efficiency and advancing agricultural modernization.

3. Results

The estimated results in Table 3 show that the Wald test values for equation independence are 6.13, 17.19, and 16.81. These values reject the null hypothesis of independence between the selection and outcome equations at the 5% significance level, indicating a correlation between the error terms in the adoption equation of ASSs and the land transfer decision equation. Additionally, the coefficients for ρ_1 or ρ_0 in Table 3 are significantly negative, suggesting the presence of negative selection bias in the sample due to unobserved heterogeneity [29]. Ignoring this bias could lead to an underestimation of the impact of ASSs on land transfer behavior.

Table 3. Estimation results of the impact factors on ASSs and land transfer choice.

Variable	Selection Equation	LTP		LTA		LTW	
	(1) ASS	(2) Adopter	(3) Non-Adopter	(4) Adopter	(5) Non-Adopter	(6) Adopter	(7) Non-Adopter
Gender	0.331 **	0.571 ***	−0.179	−0.003	−0.126	0.279	0.309
	(0.165)	(0.213)	(0.404)	(0.198)	(0.378)	(0.212)	(0.323)
Age	−0.033	−0.008	−0.038	−0.052	−0.037	−0.209 ***	−0.371 ***
	(0.032)	(0.072)	(0.096)	(0.045)	(0.074)	(0.047)	(0.102)
Age squre	1.076	−0.495	0.791	1.022	0.483	3.409 ***	7.217 ***
	(0.705)	(1.765)	(2.698)	(0.968)	(1.726)	(1.042)	(2.023)
Education	0.071 ***	−0.060 *	−0.031	−0.040	−0.057	0.006	0.034
	(0.021)	(0.033)	(0.061)	(0.025)	(0.063)	(0.024)	(0.052)
Family size	−0.010 *	−0.015 **	0.008	−0.021 ***	−0.002	0.002	−0.032 **
	(0.006)	(0.007)	(0.022)	(0.007)	(0.017)	(0.006)	(0.013)
Off-farm	−0.006	−0.027	−0.030	0.054	−0.005	−0.008	0.003
	(0.034)	(0.042)	(0.061)	(0.044)	(0.063)	(0.043)	(0.073)
Agri- experience	0.006	−0.086	0.055	−0.231 ***	0.210	0.089	0.038
	(0.076)	(0.101)	(0.121)	(0.073)	(0.207)	(0.091)	(0.155)

Table 3. *Cont.*

Variable	Selection Equation		LTP	LTA		LTW	
	(1) ASS	(2) Adopter	(3) Non-Adopter	(4) Adopter	(5) Non-Adopter	(6) Adopter	(7) Non-Adopter
Own vehicles	0.372 ***	0.258	0.185	−0.098	0.292	−0.159	0.799 **
	(0.128)	(0.184)	(0.861)	(0.167)	(0.380)	(0.157)	(0.323)
Wi-Fi	0.027	0.026	−0.005	0.026 *	−0.012	0.027	0.027
	(0.018)	(0.026)	(0.036)	(0.015)	(0.042)	(0.018)	(0.040)
Distance	0.131	−0.199	−0.612	0.494 ***	−0.377	0.475 ***	0.219
	(0.124)	(0.172)	(0.559)	(0.140)	(0.320)	(0.153)	(0.297)
Soil quality	0.096	0.148	0.078	−0.017	0.265	−0.099	0.794 ***
	(0.105)	(0.138)	(0.468)	(0.113)	(0.409)	(0.122)	(0.299)
Terrain	−0.358 **	−0.778 ***	−0.081	−0.580 ***	−0.770	−0.727 ***	−1.129 **
	(0.175)	(0.254)	(0.996)	(0.215)	(0.480)	(0.178)	(0.542)
Region	control	control	control	control	control	control	control
IV	2.255 ***						
	(0.566)						
Constant	−8.575 **	6.971	0.740	0.119	−1.025	−14.641 **	−37.076 ***
	(4.149)	(10.244)	(0.815)	(5.393)	(9.900)	(5.863)	(11.194)
ρ_1	−0.902 ***			−1.305 ***			−12.260 ***
	(0.298)			(0.368)			(1.262)
ρ_0	−1.221				−0.869		0.577
	(3.280)				(0.635)		(0.758)
$ln(\sigma_{1\mu})$				0.502 ***			
				(0.050)			
$ln(\sigma_{0\mu})$					0.532 **		
					(0.247)		
Good. Of fit test		146.30 ***		131.14 ***		171.46 ***	
Wald Test for Eq. Indep.		5.41 **		12.99 ***		8.95 **	
Obs.	858						

Note: (1) *, **, and *** sub-tables represent estimates that are significant at the 10%, 5%, and 1% levels; (2) robust standard errors are in parentheses.

Moreover, the goodness-of-fit test values for all models are significant at the 1% level, further confirming the robustness of the model. In summary, the use of an endogenous switching model to assess the impact of ASSs on land transfer behavior is both appropriate and justified. This approach effectively addresses selection bias from individual characteristics and external environmental factors, providing a more accurate estimate of the net effect of ASSs on farmers' land transfer decisions.

3.1. Analysis of Factors Influencing the Adoption of ASSs

Column (1) in Table 3 displays the results for factors influencing farmers' decisions to adopt ASSs. A close analysis shows that adoption is strongly affected by the household head's age, education, agricultural experience, motor vehicle ownership, and peer adoption behavior. The gender of the household head has a significant positive coefficient, suggesting that, under similar conditions, male heads are more likely to adopt these services than female heads. On the other hand, agricultural experience has a negative effect, with farmers who have more years of experience tending to stick to traditional methods and showing less interest in new services. The ownership of motor vehicles also positively influences adoption, as it facilitates easier access to ASSs. Finally, peer behavior in the same township plays a significant role, with the adoption choices of nearby farmers encouraging others to follow suit, demonstrating a contagion effect.

3.2. Analysis of Factors Influencing Land Transfer Decisions

Columns (2, 3), (4, 5), and (6, 7) of Table 3 show the factors influencing land transfer participation, transfer scale, and future transfer intentions. A detailed analysis reveals that, among farmers who adopt ASSs, the gender of the household head has a significant positive effect on land transfer behavior, with male heads being more likely to transfer land than female heads. The age of the household head, however, has a significant negative impact on land transfer participation and future transfer intentions. This may be due to physical limitations and reduced agricultural skills with age, which make older farmers

less willing to transfer land. For service adopters, the number of family members working off-farm negatively affects the scale of land transfer. This is likely because more off-farm employment reduces the labor available for agriculture, limiting the potential for expanding land transfers.

For both service adopters and non-adopters, farming experience has a negative impact on land transfer decisions. Farmers with more experience may prefer traditional, small-scale farming and are less motivated to engage in large-scale operations. Soil quality positively affects service adopters, indicating that farmers are more likely to transfer land with fertile soil, which supports expanding the land transfer scale and increasing future transfer intentions. For non-adopters, owning a motor vehicle has a significant positive impact on land transfer decisions. This likely facilitates better access to information about land transfer opportunities and improves the transport of agricultural goods, thus encouraging land transfers. The terrain variable has a negative effect on land transfer choices among service adopters.

3.3. Average Treatment Effect Estimation Results

After estimating the parameters of the joint choice and outcome equations, the endogenous switching regression model can calculate the Average Treatment Effect on the Treated (ATT) for the treatment group, as presented in Table 4. Unlike the mean difference analysis in Table 2, the endogenous switching probit model controls for selection biases due to both observable and unobservable factors. This adjustment allows for more accurate estimates of how adopting ASSs influences farmers' decisions to engage in land transfer.

Table 4. Estimated results of average treatment effect (ESM).

Items	ASS Adopters	ASS Non-Adopters	Treatment Effect	t-Value
LTP	0.931 (0.004)	0.082 (0.003)	0.849 (0.004) ***	190.761
LTA	4.444 (0.039)	1.920 (0.035)	3.182 (0.042) ***	47.812
LTW	0.872 (0.008)	0.854 (0.009)	0.018 (0.007) ***	2.692

Note: (1) *** indicates significant at the 1% level; (2) Robust standard errors in parentheses.

The ATT estimation results in Table 4 show three key findings. First, adopting ASSs significantly increases the likelihood of land transfer participation, raising the probability by 13.7%. Second, service adoption substantially expands the area of land transferred, with a 74.34% increase. This highlights the critical role of policies promoting ASSs, which are essential for advancing agricultural scale operations. Third, adopting these services significantly enhances farmers' willingness to transfer land in the future. The ATT value of 0.042 suggests that without adopting these services, farmers' probability of transferring land in the future would decrease by 4.2%. These results confirm that ASSs play a vital role in encouraging land transfer decisions, validating Hypotheses 1, 2, and 3.

3.4. Robustness Tests

To ensure the robustness of the estimation results, this study applies the Propensity Score Matching (PSM) method to re-assess the impact of adopting ASSs on farmers' land transfer decisions. Two common matching techniques—nearest neighbor match and kernel match—are used to estimate the ATT, with the results detailed in Table 5. Both methods confirm that the adoption of ASSs has a significantly positive effect on farmers' land transfer decisions at the 1% statistical level. These findings further validate the reliability of the previous estimation results.

Table 5. Estimated results of average treatment effect (PSM).

Items	Nearest Neighbor Match	Z-Value	Kernel Match	Z-Value
LTP	0.235 (0.0) ***	4.46	0.257 (0.050) ***	5.125
LTA	2.891 (0.278) ***	10.40	2.835 (0.214) ***	13.882
LTW	0.257 (0.073) ***	3.51	0.257 (0.056) ***	4.563

Note: (1) *** indicates significant at the 1% level; (2) robust standard errors in parentheses.

3.5. Further Analysis

To analyze the varied effects of ASSs on farmers' land transfer decisions, this study uses an endogeneity transformation model to estimate the ATT. The analysis focuses on different components of ASSs, including input supply, credit, technology, and machinery services. These estimates assess the impact of ASSs on three aspects of land transfer: participation (LTP), area (LTA), and willingness (LTW). The results in Table 6 show that, for all types of ASSs, service adoption has a statistically significant positive effect on farmers' land transfer decisions.

Table 6. Segmented effects of ASSs on land transfer decisions: ESM.

Variables	Category	Adopters	Non-Adopters	ATT	t-Value
AMS	LTP	0.925 (0.005)	0.852 (0.009)	0.073 (0.008) ***	9.402
	LTA	4.494 (0.039)	2.593 (0.065)	3.543 (0.048) ***	24.870
	LTW	0.966 (0.004)	0.855 (0.008)	0.111 (0.008) ***	13.666
ACS	LTP	0.976 (0.005)	0.355 (0.014)	0.622 (0.011) ***	47.147
	LTA	5.114 (0.045)	2.092 (0.070)	3.022 (0.083) ***	36.255
	LTW	0.889 (0.008)	0.095 (0.009)	0.793 (0.010) ***	81.642
ATS	LTP	0.953 (0.004)	0.907 (0.006)	0.046 (0.006) ***	7.214
	LTA	4.454 (0.055)	3.740 (0.052)	1.428 (0.076) ***	18.836
	LTW	0.880 (0.008)	0.771 (0.011)	0.109 (0.005) ***	24.197
AMA	LTP	0.975 (0.002)	0.877 (0.008)	0.098 (0.007) ***	13.537
	LTA	4.357 (0.036)	3.627 (0.073)	3.992 (0.042) ***	8.932
	LTW	0.858 (0.009)	0.621 (0.011)	0.237 (0.011) ***	21.405

Note: *** indicate significance levels at 1%. Robust standard errors in parentheses.

Specifically, beginning with agricultural input supply services (AMSs), the ATT estimations for the treatment group—those who have adopted AMSs—demonstrate that the adoption can enhance the rate of land transfer participation (LTP) by 6.7%, amplify the land transfer area (LTA) by a factor of approximately 1.36, and boost the likelihood of future land transfer willingness (LTW) by 32.6%. Moving to agricultural credit services (ACSs), the ATT estimations suggest that ACS adoption significantly raises the rates of LTP and LTW by 72.9% and 32.5%, respectively, and nearly doubles the LTA. Thirdly, concerning agricultural technical services (ATSs), the ATT results indicate that ATS adoption can escalate the rates of LTP and LTW by 27.6% and 10.6%, respectively, and increase the LTA by a factor of approximately 1.26. Lastly, for agricultural machinery services (AMAs), the ATT estimations reveal that AMA adoption markedly augments the rates of LTP and LTW by 11.7% and 26.3%, respectively, and enhances the LTA by nearly 1.11 times. These findings highlight that adopting ASSs, both comprehensively and for specific types, increases farmers' likelihood of transferring land, expands the scale of land transfer, and enhances their willingness to participate in land transfer. Consequently, Hypothesis 4 is substantiated.

Notably, a comparative analysis of the outcomes across the four groups yields intriguing insights. When examining the effect on LTP, ACSs exhibit the most substantial impact,

with an average absolute treatment effect (ATE) of 72.9%, followed by ATSs at 27.6%, AMAs at 11.7%, and AMSs with the least impact at 6.7%. Secondly, concerning the influence on the LTA, the descending order of the intensity of impact among the four service types is as follows: AMS (ATT value of 136.2%), AMA (ATT value of 111.43%), ACS (ATT value of 150.14%), and ATS (ATT value of 126.47%). Lastly, when assessing the impact on the LTW, the descending order of influence among the four service types is ACS (ATT value of 32.5%), AMS (ATT value of 32.6%), AMA (ATT value of 26.3%), and ATS (ATT value of 10.6%). In summary, ACSs appear to have the most pronounced impact on farmers' land transfer decisions. This finding aligns with the research of Abdallah [33] and Cerulli and Ventura [34], which highlight that farmers face significant capital constraints in the pursuit of scale operations and urgently require financial relief during the agricultural production process. These services, particularly credit services, are instrumental in alleviating these financial pressures and thus significantly influence land transfer decisions.

4. Discussions

This study makes several innovative contributions to the analysis of how agricultural socialized services (ASSs) affect land transfer. Firstly, it constructs a three-stage dynamic analytical framework that encompasses participation decisions, scale decisions, and future intentions regarding land transfer. This framework breaks away from the limitations of traditional single-dimensional studies, offering a more comprehensive perspective on land transfer decisions. Secondly, this study pioneeringly employs endogenous switching probit and regression models, using township-level service usage rates as instrumental variables to address endogeneity issues. This methodological approach allows for a systematic examination of the multidimensional impacts of ASSs on land transfer. Thirdly, the analysis identifies differentiated influencing factors, such as the household head's age, education level, off-farm employment, and terrain conditions, revealing how individual characteristics and geographic environment interact to affect service adoption and land transfer behavior. Additionally, this study further explores the distinct impacts of various service components on land transfer. Overall, this approach provides a more nuanced understanding of the mechanisms underlying land transfer decisions and highlights the essential role of ASSs in promoting land transfer and agricultural scale operations.

4.1. Key Findings

We briefly discuss key findings from our empirical results. As seen above in Table 3, our empirical results reveal that he adoption of ASSs significantly increases farmers' likelihood of participating in land transfer, which is consistent with the findings of Yang et al. [35]. The results also demonstrate a positive impact of ASS adoption on the expansion of land transfer areas, echoing the conclusions of Jiang et al. [36] that such services positively influence land transfer and large-scale farming operations. Additionally, male-headed households tend to be more likely to transfer in land compared to their female counterparts. This may be due to differences in decision-making and risk preferences between genders. These findings align with Feng et al. [3] on their findings on a set of households in China. The empirical results further reveal that the higher the number of family members engaged in off-farm work, the higher the tendency for households to participate in land transfers. Kousar and Abdulai [29] report similar findings in their study on Pakistani farmers by observing that increased off-farm employment reduces the likelihood of land transfers. We also find household head's level of education to be positively related to ASS adoption, suggesting that households with higher level of formal education have the higher tendency of openness to new technologies and practices, a finding consistent with the conclusions of Zhu and Ma et al. [37]. Moreover, farm households in hilly or mountainous areas exhibit a

lower willingness to transfer land, likely due to the constraints of complex terrain on large-scale agricultural operations. This finding is consistent with the research of Deng et al. [38], who noted that such terrain conditions hinder large-scale agricultural operations, resulting in smaller land transfer scales in these regions.

4.2. Policy Recommendations

Based on the research findings, the following policy implications can be derived. ASSs hold significant potential for advancing agricultural modernization, optimizing land resource allocation, and promoting sustainable agricultural development. However, realizing this potential requires coordinated efforts from both governmental and farmer perspectives.

From a governmental perspective, it is crucial to design top-level policies that align with agricultural and rural development trends, guiding the orderly expansion of these services and land transfer. Specific measures are as follows: developing targeted subsidy programs for different ASS types to encourage service expansion and quality improvement; enhancing policy support through financial aid, tax breaks, and technical guidance; establishing risk-sharing mechanisms for agricultural production to alleviate farmers' concerns; strengthening land transfer market regulation for transparency and fairness; investing in agricultural infrastructure construction; and creating agricultural service information platforms to improve information flow between providers and farmers.

From the farmers' perspective, enhancing agricultural education and training is essential to improve knowledge of modern farming techniques and facilitate access to ASSs. This can be complemented by upgrading production infrastructure; encouraging participation in agricultural cooperatives and professional organizations to strengthen connections with service providers; supporting the adoption of new technologies and management practices to boost productivity and income; and providing more information and technical assistance to help farmers make informed decisions about ASS adoption. By integrating these measures, the potential of ASSs can be fully realized, land resources can be better allocated, agricultural modernization can be promoted, and sustainable agricultural development can be achieved.

4.3. Research Limitations

This study acknowledges several limitations that should be addressed in future research. This study uses cross-sectional data from Sichuan Province, limiting generalizability to other regions or temporal contexts. Additionally, service quality data were unavailable, which we aim to address with granular data in future research. Future research could extend this framework using panel data to examine long-term behavioral changes, incorporate digital agricultural services emerging in China, and conduct cross-regional comparisons. Exploring climate change risks and policy interventions would enhance practical relevance, while integrating qualitative methods would strengthen theoretical insights into land transfer dynamics under agricultural modernization.

5. Conclusions

This study develops an analytical framework for farmers' land transfer decisions, consisting of three stages: participation, scale, and future intention. Using data from 858 farmers in Sichuan Province in 2020, this study applies endogenous switching probit and regression models to control for selection biases from both observable and unobservable factors. The analysis shows that adopting ASSs significantly promotes land transfer. Participation rates increased by 13.7%, the transferred area expanded by 74.34%, and the

likelihood of future transfers rose by 4.2%. Robustness checks with the PSM method confirm the reliability of these findings. This study also reveals that factors such as the age and education level of the household head and motor vehicle ownership positively influence the adoption of ASSs. Conversely, land transfer behavior is affected by variables such as the household head's age, non-agricultural employment among family members, soil quality, terrain, and distance to the nearest market. These findings provide new insights into the mechanisms behind service adoption and emphasize the importance of individual characteristics and social networks in promoting ASSs. Further analysis identifies agricultural credit services as having the greatest impact on land transfer, confirming that capital is a critical factor in agricultural production and management. These conclusions highlight the essential role of ASSs in promoting land transfer and agricultural scale operations.

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