Supporting Materials

S1. Control Variables

S1.1 Control Variable Characteristics

The basic characteristics of households in the sample are as follows: 27% of the sampled households transfer in land, with an average rented land area of 1.35 Mu per household. Regarding the individual characteristics of household heads, the majority are male; the average age is 54.68 years, indicating an aging population; household heads generally have a low level of education, with an average of 7.78 years of schooling, equivalent to junior high school level. In terms of family characteristics, 20% of the households have political affiliations. On average, fewer than 2 individuals in a household are engaged in agricultural activities, but they spend more than half a year in agricultural activities, indicating that agriculture remains the primary choice for households. The average income from agricultural cultivation is 48,000 CHY[①]. [The data collection period extends until Dec 2019.]

S1.2 Interpretation of the Regression Results for Control Variables

Regarding control variables related to household family characteristics, there is a tendency for household heads who are older to be less inclined towards renting larger plots of land. Household income level has a negative coefficient in the inflow equation and a positive coefficient in the transfer-out equation, with statistical significance at 5% and 1%, respectively. This indicates that households with higher income levels are less inclined to transfer in land; instead, they prefer to transfer out land. However, once the decision to rent land is made, there is a higher probability of leasing a larger-scale land. Additionally, family agricultural income contributes to the tendency of households to transfer in land. Still, the area of transfer land is constrained by various external factors such as land adjustments, geographical location, and the willingness of other farmers to transfer land, resulting in insignificant estimation results.

Empirical results focusing on village-level variables indicate that the proportion of households participating in land transfer in the village contributes to land transfer. This suggests that in villages with more active land transfer, households are more likely to transfer land and are more likely to transfer a greater area of land. The land transfer market passes a significance test at 10% in the inflow area equation, indicating that the land market is more likely to facilitate the land transfer-in but has a relatively minor impact on the behavior of transfer land. This implies that promoting the active development of rural land transfer markets through appropriate institutional arrangements can facilitate optimal land allocation and achieve economies of scale in land operation.

[①] Crop income refers to the total revenue obtained by farmers from selling agricultural products, and does not account for net income after deducting production inputs such as agricultural materials and hired labor.

The significance of the estimated results for individual variables is not entirely satisfactory. Having political affiliations does not significantly alter the land resource allocation behavior of such households. Furthermore, family characteristics such as the number of individuals engaged in agriculture, agricultural input time, and whether the family has split do not have a significant impact on land transfer. This may be because the expansion of land relies primarily on empowering farmers through modern agriculture, transferring technology, management, and agricultural inputs to farmers, assisting them in field management, and ensuring normal production after expanding land scale, with minimal requirements on family conditions. Village-level variables related to land tenure, land adjustment, and the need for collective approval for land transfer are also not significant. This is due to the fact that land transfer and the administrative adjustment of land are two different mechanisms, and they do not directly establish a causal relationship. Moreover, leading agricultural enterprises in modern agriculture have already made institutional arrangements for land, coordinating restrictions on land transfer with administrative departments in advance to ensure the scale development of modern agriculture. In the Wald joint significance test, the rejection of the null hypothesis "all province dummy variables are zero" suggests the need to control for regional effects of provinces in the regression.

S2. Calculation of Technical Efficiency

Due to the heterogeneity in the productivity levels of farmers, land allocation tends to flow from actors with low production efficiency to those with high production efficiency. On the left side of the "inverted U-shaped" turning point, there is a positive correlation between production efficiency and land scale. Given that the average land area per household in this study is 18.37 mu (see Appendix Table 1), most farmers' land scale is far from the efficiency margin. Therefore, according to the above theory, this paper takes farmers' production efficiency as the dependent variable, replacing the behavior and area of farmers' inflow for Tobit regression. This is done to estimate the relationship between modern agriculture and farmers' production efficiency and further determine the direction of land transfer. Farmers' production efficiency is generally represented by the Technical Efficiency (TE) index, reflecting the size of farmers' production capacity. The estimation of TE values often involves the use of the Stochastic Frontier Analysis (SFA) method. In this study, the Cobb-Douglas function is employed for estimation. Initially, it is necessary to test the assumption of constant returns to scale in the C-D production function. Subsequently, the Maximum Likelihood (ML) method is used to estimate farmers' technical efficiency. Finally, the obtained technical efficiency is used to replace the dependent variable.

Table S1: Agricultural Land Operation Situation of the Survey Sample in 2019

Item	Sample Size	Mean	Standard	Minimum	Maximum
Contracted Land Total Area (mu)	1170	4.62	7.34	0	100
2019-End Operational Land (mu)	1176	18.37	125.76	0	4000
Contracted Land	1170	4.39	6.75	0	100

Contracted Collective Mechanized Land	1193	0.23	1.93	0	50
Transfer-in Land	1193	8.58	123.31	0	4000

Data Source: The author compiled the data based on cleaned survey data.

Note: There is a small amount of missing data for some variables.

Table S2: Descriptive Statistics of Cobb-Douglas Production Function

Item	variable	Definition or Measurement	Mean	Standard
Input-output variables	Total output	Total income from planting(CHY)	48069.00	449608.00
	Capital investment	Total production costs of planting(CHY)	18606.51	142561.2
	labor input	Labors input for planting, labors × day	82.24	467.10
	land input	Total crop area of planting(Mu)	43.11	268.90
	Farmer production efficiency	The technical efficiency of farmers' planting production is estimated using the SFA model.	0.77	0.10

Table S3. Descriptive Statistics of Farmers' Production Technical Efficiency

Item	Sample Size	Mean	Standard Error	Minimum	Maximum
Farmer production technical efficiency α	847	0.773	0.097	0.097	0.924

Firstly, conduct a test for the assumption of constant returns to scale. If it is determined to estimate the technical efficiency of the production function using a stochastic frontier model, a hypothesis needs to be tested beforehand, namely that the production function for farmers exhibits constant returns to scale. It is noteworthy that due to the significant influence of village-level factors on land transfer, village-level dummy variables are introduced into the model during estimation to control for factors at the village-level that cannot be explicitly measured or reflected (such as local economic conditions, climate resources, land quality, air pollution, etc.). Stata15 software is employed for stochastic frontier analysis (SFA) of the production function[②]. Wald tests are conducted separately for village-level dummy variables. The estimated value for the dummy variable indicating whether land tenure is established in the village is 0.0507 (0.1072), with a *p*-value of 0.6364; the estimated value for the dummy variable indicating whether land adjustment occurs in the village is

[②] Village-level dummy variables do not exhibit joint significance, with a $\chi 2$ value of 3.90 and a p-value of 0.1421 in the Wald joint test, indicating that the null hypothesis (at least one of the village-level dummy variables is zero) cannot be rejected. The inability to reject the null hypothesis suggests that both dummy variables might be zero, or one of them may not be zero. Further assessment is needed to determine the potential significance of one of the dummy variables to some extent

0.1611 (0.0850), with a *p*-value of 0.0579. It is found that the dummy variable for land adjustment is significant at the 10% level. Given this, in the more rigorous estimation analysis of the stochastic frontier production function below, consideration is given to controlling for all village-level dummy variables. The table below provides the estimated output elasticity and related parameters or estimates of the input factors, land, labor, and capital that is logarithmic transformation in the Cobb-Douglas production function. The χ^2 statistic for the Wald test is 0.00, with an associated p-value of 0.9555, indicating that the null hypothesis of constant returns to scale (sum of coefficients equal to 1) cannot be rejected. This test result aligns with the general economic perspective on constant returns to scale in agriculture.

Table S4. Cobb-Douglas production function estimation results

Item	Coefficient	Standard Error
Output Elasticity		
Land S (logarithm)	0.3849^{***}	0.0344
Labor force L (logarithm)	0.1221^{***}	0.0182
Capital K (logarithm)	0.4919^{***}	0.0330
intercept term	3.8684^{***}	0.2321
Variance parameter		
σ^2	0.3337	0.0188
σ_u	0.2956	0.0321
σ_v	0.4963	0.0266
$\lambda=\sigma_u/\sigma_v$	0.5956	0.0454
Diagnostics and other information		
Log likelihood	-735.2145	
One-sided generalized LR test (H_0: σ_u=0)	23.28[0.0000]	
Wald constraint checking（χ^2）	0.00 [0.9555]	
sample size	847	

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. [ ] denotes the corresponding probability (p-value) for each test. Due to space constraints, the reporting of results for village-level dummy variables is omitted and replaced with annotation reporting

Next, we adopt the stochastic frontier model to estimate the efficiency of farm production. Based on the earlier test results indicating constant returns to scale in the agricultural production function, the intensive form of the Cobb-Douglas (C-D) production function, excluding labor and capital inputs, is obtained to represent input-output relationships. Using Stata15 software, ML estimates for the SFA model in the intensive form of the C-D production function are calculated (as shown in the table below). Additionally, OLS estimates for the intensive form of the C-D production function as the frontier production function are also reported. A comparison of parameter estimates between the two models reveals that both methods yield generally desirable results. The estimated parameters for explanatory variables are very close, and their significance is mostly consistent, indicating the robustness of the assumptions regarding the farm production function.

The SFA model incorporates inefficiency terms, whereas OLS attributes such explanatory variations to other explanatory variables. Through a one-sided generalized likelihood ratio test for inefficiency terms, the LR is significant at the 1% level, rejecting the null hypothesis "σu=0," indicating the presence of inefficiency terms in the sample data. Since the OLS estimation of the production function does not assume an inefficient state, the use of the SFA method for relative necessity is justified. The estimation results of the SFA model reveal that the proportion of the composite variance attributed to technical inefficiency variance (λ) is 0.5958, significant at the 1% level through a significance test③. This implies the existence of technical inefficiency among sampled farmers, making ML estimation using the SFA model superior to the traditional OLS estimation of the average production function.

Based on the estimation results of the SFA model, the agricultural production efficiency level α for each farmer is represented by the technical efficiency index TE. Examining TE reveals significant differences in production efficiency among farmers④, with a maximum value of 0.9241 and a minimum of only 0.0966. Due to the substantial disparities in farm production efficiency, possibilities for land mobility are provided, offering motivation to address distortions in land resource allocation.

Table S5. Stochastic frontier production function estimation results

Item	OLS	SFA
Stochastic frontier production function		
Average labor input per mu (L/S, logarithm)	0.1227***(0.0166)	0.1228***(0.0133)
Average capital investment per mu (K/S, logarithm)	0.4859***(0.0575)	0.4916***(0.0327)
Land title confirmation dummy variable	0.0247(0.0827)	0.0500(0.1064)
Land adjustment dummy variable	0.1804**(0.0796)	0.1607*(0.0846)
intercept term	3.6309***(0.3783)	3.8673***(0.2313)
Variance parameter		
σ_u	—	0.2957***（0.0321）
σ_v	—	0.4963***（0.0188）
$\lambda=\sigma_u/\sigma_v$	—	0.5958***（0.0177）
Diagnostics and other information		
Log likelihood	—	-735.21609
One-sided generalized LR test (H_0: σ_u=0)	—	23.40[0.0000]
Land title confirmation dummy variable Wald test	0.09[0.7655]	0.22[0.6388]
Land adjustment dummy variable Wald test	5.13[0.0235]	3.16[0.0575]
sample size	847	847

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. ( ) is the heteroskedasticity-robust standard error, and [ ] is the probability p value of the corresponding test.

S3. PSM inspection

This study adopts agricultural production revenue (net income from planting) as the measure. There are two main reasons for this: first, there are restrictions on the planted crop varieties, and different varieties reflect significant differences in output; second, during the research, it was found that some leading enterprises in modern AVC to ensure the circulation of production materials within their value chain and increase the default costs for both parties, not only raised the prices of agricultural inputs but also increased the purchase prices of agricultural

③ The p-value associated with the significance test of λ is 0.0000.
④ The mean of TE is 0.7731, with a standard error of 0.0971.

products. Although this largely ensures the fulfillment rate of both parties, it makes it challenging for the income of farmers to objectively reflect their actual output levels. In fact, one of the important purposes of farmers integrating into AVC is the increase in net income. Therefore, this study takes net income from planting, which is the net income obtained by subtracting agricultural expenses from agricultural income, to compare the agricultural output levels between groups.

To ensure the quality of matching and the reliability of estimation results, it is necessary to conduct tests for the balance between the treatment group and the control group and the common support domain assumption before estimating the relevant effects.

(1) Balance test

This study examines the balance of matching from three aspects (Rubin, 2001): first, compare the standardized deviation of variables between the treatment group and the control group before and after matching; a reduction in deviation indicates a decrease in group differences. Second, compare the means of matching variables between the treatment group and the control group to see if there is a significant difference. If the null hypothesis cannot be rejected (no significant difference between groups), then there is no significant difference between groups. Third, examine PseR2, LR, mean deviation, median deviation, B value, and R value to overall judge whether the balance test meets assumptions.

Using three methods of balance testing (nearest neighbor matching, caliper matching, kernel matching), the results of the balance test (shown in the table below) after matching show that the mean deviation and median deviation between the treatment group and the control group have significantly decreased, both falling below the 5% standard (Rosenbaum and Rubin, 1985), indicating that matching has reduced overall bias. The group differences of most variables have gradually become non-significant after matching, indicating that matching has reduced group differences. Pseudo R2, LR statistic, and B value have all significantly decreased, while R value has slightly increased. The B values after matching are all below the 25% standard, indicating that the overall matching effect is good. Overall, matching significantly reduces the differences between the treatment group and the control group, minimizes sample selection bias, and largely satisfies the balance assumption, making the sample matching quite successful.

Table S6. Test results of PSM balance hypothesis

matching method	Pseudo R^2	LR	P-value	mean deviation %	median deviation %	B	R
Before matching	0.0059	41.06	0.000	21.90	22.1	61.0*	1.14
nearest neighbor matching	0.003	1.01	0.998	3.80	3.1	12.3	1.17
Caliper match	0.003	0.92	0.999	2.10	0.30	12.1	1.22
Kernel matching	0.003	1.09	0.998	3.80	2.90	12.8	1.18

Note: The B value represents the standardized difference in the mean deviation between the treatment group and the control group, and the R value represents the ratio of the mean deviation value and the variance value between the treatment group and the control group; the B value is less than 25%, and the R value is within [0.5, 2], the matching quality is higher.

(2) Common support domain test. Through the balance test and the common support domain test, out of 1193 samples, 746 observations fall within the common value range⑤. For ATT, ATU, and ATE, at least one is statistically significant at the 10% level. The score interval for ATT is within the range [0.010, 0.557]. It is easy to

⑤ It is inferred that the method used for this observational study is a result of matching with replacement, allowing for ties, using nearest neighbor matching, with k=4.

see from the graph below that after matching, there is a significant overlap between the treatment group and the control group.

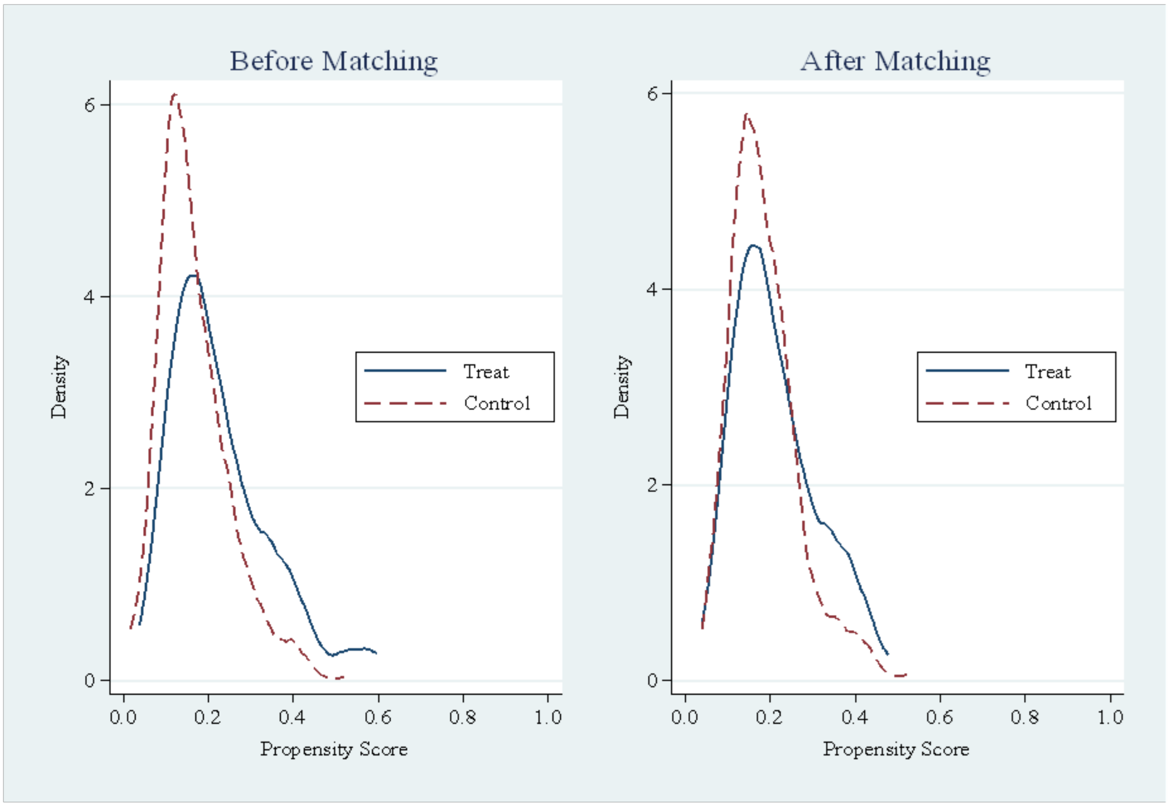

Figure S1. Probability density distribution map of PSM

References:

1.Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. The American Statistician, 39(1), 33-38.

2.Rubin, D. B. (2001). Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. Health Services and Outcomes Research Methodology, 2(3-4), 169-188.