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Analysis of the Impact of Automatic Seeding and Fertilization Technology Application on Land Output Rate and Cost Structure of Family Farms

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Abstract: This paper examines the effects of automatic seeding and fertilization technology on the land output rate and cost structure of family farms. Using the activity-based costing approach, it develops a theoretical framework of "technology application - operational efficiency - cost driver" and performs an empirical analysis with micro-data from 326 family farms. The study reveals that this technology substantially enhances the cost structure of family farms via labor cost reduction, mechanical cost substitution, and precise material cost management. The labor cost share declines from 38.7% to 21.3%, while the mechanical cost proportion rises from 12.4% to 18.6%. Additionally, fertilizer efficiency increases from 35% to 58%, and seed wastage decreases from 18% to 3%. Moreover, the impact of technology application differs based on scale and crop type. When the farm area surpasses 300 mu, the substitution effect of mechanical costs is notably strengthened; the cost optimization effect for food crops outperforms that of cash crops. The study offers a theoretical foundation and practical guidance for family farms to adopt refined cost management.

Keywords: Automatic seeding and fertilization technology; Family farms; Cost structure; Land output rate; Activity-based costing; Scale effect; Crop type difference

1. Introduction

Family farms, as the cornerstone of large-scale operation in modern agriculture, their cost control is directly related to market competitiveness. In recent years, labor costs have been increasing at an unprecedented annual rate of 12.3%.[4] The traditional extensive cost management method can no longer meet the requirements of modern development, while automatic seeding and fertilization technology has reshaped the agricultural production system through precise operation processes, providing an innovative way to optimize the cost structure. Currently, academic research mostly focuses on the specific empirical analysis of the application effects of this technology [1], but there is little systematic research on cost aspects. Existing literature basically adopts the classification form of "materials, labor, and expenses"[5], but fails to effectively integrate the quantitative analysis framework from the accounting perspective. Based on the activity-based costing method, this study constructs a theoretical model of "technology application - operation efficiency - cost driver" and conducts relevant empirical tests with 326 micro-data of family farms, aiming to explore the impact of automatic seeding and fertilization technology on the cost structure, and thus provide a reasonable basis for refined cost management.

2. Theoretical Framework and Research Hypotheses

2.1 Adaptability Analysis of Activity-Based Costing

Activity-based costing relies on the theoretical framework of "resources, activities, and cost objects", breaking through the constraints of the static allocation mode of traditional cost accounting of "materials, labor, and expenses", and is particularly suitable for exploring the dynamic changes in cost structure caused by technological innovation. In the field of family farms, after the adoption of automatic seeding and fertilization technology, the agricultural production mode has gradually changed from extensive to intensive, making the cost composition and its driving factors show diversified characteristics. The existing accounting system is difficult to accurately reflect the cost fluctuations in each operation link [5]. This method subdivides the seeding and fertilization process into five interrelated operation units: "soil testing, seed pretreatment, seeding execution, fertilization regulation, and quality inspection"[6], so as to systematically identify the cost drivers in each operation stage. Labor cost is significantly positively correlated with labor time [4]; seed cost is greatly affected by seeding accuracy [7]; fertilizer cost is closely related to nutrient absorption rate [10]; and mechanical operation cost is mainly determined by the frequency of equipment use [8]. This refined cost accounting system can not only accurately measure the cost-effectiveness of automatic seeding and fertilization technology in each operation link, but also provide empirical basis for exploring the internal mechanism of cost structure improvement driven by technology, thus providing theoretical support and operational guidance for family farms to implement accurate cost control strategies.

2.2 Mechanism of the Impact of Technology Application on Cost Structure

2.2.1 Labor Cost Squeezing Effect

The automatic seeding and fertilization system significantly reduces labor input through precise seeding and fertilization, thereby reducing the proportion of labor cost. The direct effect is that intelligent seeding equipment significantly improves operation efficiency. By achieving centimeter-level positioning accuracy to replace traditional manual seeding, the operation time per mu is shortened from 2.1 hours to 0.3 hours. Based on this calculation, with the average agricultural labor cost of 82 yuan/hour in 2023, the unit operation cost is significantly reduced from 172 yuan to 24.6 yuan, achieving a cost saving of up to 85.7%. This efficiency improvement shows a cumulative effect in large-scale agricultural operations. For example, a farm with an area of 300 mu is expected to save about 44,000 yuan in quarterly labor costs. The indirect effect is due to the innovation of seeding technology. By accurately controlling the seeding spacing error to $\leqslant$2cm [9], the error rate is significantly reduced by 75% compared with manual operation. This improvement reduces the rework rate from 15% in the traditional operation mode [3] to less than 3%, thus reducing the labor demand in the quality inspection stage and achieving about 40% labor cost saving. When discussing the impact of "quantity" and "quality" dual-dimensional optimization strategies on the labor cost structure, compared with the traditional operation mode, after the introduction of technical solutions, the proportion of labor cost significantly decreases from 38.7% to 21.3%, which is based on descriptive statistical analysis. This result strongly supports Hypothesis H1, that is, there is a positive relationship between the improvement of technology penetration rate and the reduction of labor cost.

2.2.2 Mechanical Cost Substitution Effect

The introduction of automatic seeding and fertilization system, through the fixed cost formed by equipment investment, has a significant substitution effect on the variable cost dependent on labor. The specific threshold of this substitution effect, i.e., the critical point, depends on the scale effect of agricultural operations.[2] Taking an intelligent seeder with an initial cost of 150,000 yuan as an example. If the straight-line depreciation method is adopted, its annual depreciation cost is 28,500 yuan. Considering the residual value rate of 5%, the unit depreciation cost drops to 95 yuan/mu after completing 300 mu of operations, which is lower than the cost of traditional manual operation for the first time. The identification of this critical scale confirms Hypothesis H2, that is, when the land area exceeds 300 mu, the marginal substitution effect of mechanical cost shows a significant amplification trend. Further analysis reveals that when the scale of farmland operations is expanded to 500 mu, the unit mechanical operation cost drops to 57 yuan/mu, achieving a significant saving of 66.9% compared with labor cost. In the total production cost composition, the proportion of mechanization cost also increases from the original 12.4% to 18.6%. This substitution effect shows obvious regional differences in terrain characteristics, especially between hilly areas and plain areas. In plain areas, the large-scale intensive farming mode significantly improves the use efficiency of agricultural machinery, with the equipment utilization rate as high as 85% [8]. In contrast, the scattered land plots in hilly areas limit the continuity of agricultural machinery operations, and the unit mechanical cost increases by 23%, which further highlights the key role of the principle of economies of scale in promoting the substitution effect.

2.2.3 Material Cost Precision Effect

The automatic seeding and fertilization system effectively reduces material waste through the implementation of a two-layer precise control strategy. According to the research of Tran et al. (2024), the variable fertilization system can dynamically adjust the fertilization strategy according to the real-time detection data of soil nutrients, significantly improving the fertilizer utilization efficiency. Compared with the traditional fertilization mode, the fertilizer utilization rate is significantly increased from 35% to 58%, achieving a reduction in fertilizer input per unit area, specifically by about 23%[10]. Taking corn planting as an example, in the traditional fertilization mode, 40 kg of compound fertilizer is needed per mu, corresponding to a cost of 240 yuan. In contrast, after the implementation of intelligent fertilization technology, the fertilizer usage per mu is significantly reduced to 30.8 kg, and the corresponding cost is reduced to 185 yuan, achieving an economic effect of saving 55 yuan per mu. The reduction in seed cost is mainly due to the application of precise seeding technology, which realizes precise control of seeding depth and reasonable spacing between seeds with the help of a pneumatic seed metering device. This innovative measure significantly reduces the seed waste rate from 18% in the traditional manual seeding mode[7] to less than 3%, and thus saves about 30 yuan per mu in seed cost. This study reveals that in the cost optimization of cash crop planting, especially when the seed cost is high, the implementation of precise seeding technology can significantly reduce the seed loss cost, estimated to be about 150 yuan per mu. Due to the complexity of the fertilization demand of cash crops, their fertilizer optimization effect is relatively limited compared with food crops, with an increase of only about 8 percentage points. This finding strongly supports the assertion in Hypothesis H3 that the cost optimization effect of cash crops is weaker than that of other crops.

3. Research Design

3.1 Sample Selection

This study implemented a multi-stage stratified random sampling technique to ensure the representativeness and comprehensiveness of the sample. In the first stage, according to the popularization degree of agricultural mechanization, the country was divided into three levels of regions: eastern, central, and western. Then, in each type of region, 4 major agricultural production provinces were randomly selected, totaling 12 provinces, including Shandong, Jiangsu, Henan, Hubei, Sichuan, and Shaanxi. In the subsequent stage, in each selected province, family farms applying automatic seeding and fertilization technology were identified and included as the intervention group, while family farms not implementing this technology were selected as the control group. The specific conditions for including samples are as follows: the farm must have at least 3 years of operation history, the cultivated area is in the range of 20 to 500 mu to reflect the general scale of family farms, and the main crops should include food crops such as wheat, corn, and rice, or cash crops such as vegetables and fruits. Finally, a total of 326 valid samples were collected and analyzed, including 187 in the experimental group and 139 in the control group, and their specific distribution is detailed in Table 1.

Table 1: Sample Distribution.

Region	Number of Provinces	Treatment Group	Control Group	Total
Eastern	4	68	42	110
Central	4	62	51	113
Western	4	57	46	103
Total	12	187	139	326

3.2 Variable Definition

3.2.1 Explained Variable

Cost Structure Optimization (CSO): A comprehensive index is constructed using the entropy method, including 3 secondary indicators.

Calculation steps: (1) Standardize the indicators. (2) Calculate the indicator entropy and weight. (3) Weighted summation to obtain CSO.

3.2.2 Core Explanatory Variable

Technology Application Depth (TAD): Calculated by weighting three dimensions:

Equipment investment intensity (X1) = investment in automatic seeding and fertilization equipment / operating area (10,000 yuan/mu), with a weight of 0.4

Intelligent control level (X2): Assigned according to whether the equipment has GPS navigation and variable fertilization functions (0 = none, 1 = partially equipped, 2 = fully equipped), with a weight of 0.3

Operating area coverage rate (y_3) = Technical application area / Total operating area × 100%, with a weight of 0.3

Calculation formula: $TAD = 0.4 \times X_1 + 0.3 \times X_2 + 0.3 \times X_3$ (value range 0-3, the larger the value, the deeper the technology application).

3.2.3 Moderating Variables

Farm scale (S): operating area (mu); to reflect the scale effect, the square term of S (S^2) is introduced

Crop type (CT): dummy variable (1 = food crops, 0 = cash crops)

3.2.4 Control Variables

Operating years (Age): the number of years the farm has been established

Soil fertility (Fert): assigned according to the soil test report (1 = low, 2 = medium, 3 = high)

Household head's education years (Edu): the number of education year's corresponding to the household head's education level (e.g., junior high school = 9 years)

Regional characteristics (Region): dummy variable (1 = eastern, 2 = central, 3 = western)

3.3 Model Setting

Benchmark Model: $CSOi = \alpha_0 + \alpha_1 TAD_i + \sum akControl_{ki} + \mu_i$

This study takes CSO_i as the cost structure optimization level of the i-th family farm as the dependent variable, takes TADi as the core independent variable (reflecting the depth of technology application), and also adds control variables $Control_{ki}$, including operating years (Age), soil fertility (Fert), household head's education level (Edu), and regional attributes (Region). Among them, $\alpha 0$ is the intercept term, $\alpha 1$ reflects the regression effect of the core independent variable, αk corresponds to the parameter estimation value of each control variable, and μ_i is the random disturbance term. This model aims to explore the actual impact mechanism of technology application depth on cost structure optimization. If α_1 is significantly positive, it can be proved that increasing technology investment can significantly promote the effect of cost structure improvement.

Moderating Effect Model: To explore the moderating role of farm scale and crop type in the relationship between technology application and cost structure optimization, interaction terms are introduced to construct the model.

Farm Scale Moderation Model: $CSO_i = \beta_0 + \beta_1 TAD_i + \beta_2 TAD_i \times S_i + \beta_3 S_i + \beta_4 {S_i}^2 + \sum \beta k Control_{ki} + V_i$

S_i is the farm scale, $TAD_i \times Si$ is the interaction term between technology application depth and farm scale, and ${S_i}^2$ is used to capture the non-linear characteristics of the scale effect. If β_2 is significant, it indicates that the farm scale has a moderating effect on the cost optimization effect of technology application. A positive coefficient means that the expansion of scale strengthens the positive impact of technology, while a negative coefficient means weakening.

Crop Type Moderation Model: $CSO_i = \gamma_0 + \gamma_1 TAD_i + \gamma_2 TAD_i + CT_i + \gamma_3 CT_i + \sum \gamma k Control_{ki} + \varepsilon_i$

CT_i is a dummy variable for crop type (1 = food crops, 0 = cash crops), and is the interaction term between technology application depth and crop type. If γ_2 is significant, it indicates that there are differences in the cost optimization effect of technology application among different crop types. A positive coefficient indicates that the optimization effect of technology is stronger in food crops, while a negative coefficient indicates that the effect is weaker in cash crops, so as to verify the assertion about the difference in crop types in Hypothesis H3.

To explore the mechanism by which the improvement of operation efficiency caused by technology application affects the cost structure, this study selects the proportion of labor cost, mechanical cost, and material cost as mediating variables (M) to establish a mediating effect analysis model for the study.

Step 1: $M_i = \delta_0 + \delta_1 TAD_i + \sum \delta_k Control_{ki} + \zeta_i$

Step 2: $CSO_i = \theta_0 + \theta_1 TAD_i + \theta_2 M_i + \sum \theta_k Control_{ki} + \eta_i$

If the first-stage regression analysis is significant and the second-stage regression analysis is significant, and the absolute value of θ_1 is less than that in the benchmark model, it is considered that there is a partial mediating effect. This indicates that technology application indirectly affects cost structure optimization by adjusting operation efficiency (such as the proportion of labor, mechanical, and material costs), verifying the transmission path of "technology application → operation efficiency → cost driver". All established models have passed the heteroscedasticity test and multicollinearity test, ensuring the robustness of the estimation results. To address the issue of regional clustering in panel data, this paper uses cluster-robust standard errors for correction.

4. Results and Analysis

4.1 Descriptive Statistics

In the case of selecting 326 family farms for empirical analysis: the mean value of the cost structure optimization index is 0.42, with a standard deviation of 0.18, showing obvious heterogeneity and a medium to high level. The mean value of technology application degree is 1.25, indicating that there is still much room for improvement in the current automatic seeding and fertilization technology. The mean value of equipment investment intensity is 0.08 million yuan/mu, and the mean value of intelligent control system is 1.12. Although some intelligent functions are available, the proportion of high-end agricultural machinery is low. The average operating scale of the sample farms reaches 156.8 mu, including various scales, and about 23% of the farms have an area larger than 300 mu, showing a trend of scale expansion. Food crops account for 67% and cash crops account for 33%, which basically conforms to the characteristics of China's agricultural industrial structure. The average operating years are 8.2. The data sample of this study is the 2021 data sample, including 258 observation points. The average fertility is 2.1, which is "medium". The average education years of the household head is 9.6 years. The proportion of the eastern region is 33.7%, the central region is 34.7%, and the western region is 31.6%. The overall sample has high representativeness and reasonable uniformity, which can be a reliable basis for further research.

Table 2: Descriptive Statistics of Main Variables.

Variable Category	Variable Name	Mean	Standard Deviation	Minimum	Maximum
Explained Variable	Cost Structure Optimization Degree	0.42	0.18	0.05	0.89
Core Explanatory Variable	Technology Application Depth	1.25	0.76	0	3
	Equipment Investment Intensity	0.08	0.05	0	0.32
	Intelligent Control Level	1.12	0.68	0	2
Moderating Variable	Farm Scale	156.8	102.3	20	500
Control Variable	Crop Type	0.67	0.47	0	1
	Operating Years	8.2	4.5	3	25
	Soil Fertility	2.1	0.7	1	3
	Household Head's Education Years	9.6	2.3	6	16
	Regional Characteristics	2.03	0.82	1	3

4.2 Regression Result Analysis

There is a significant positive correlation between technology application depth and cost structure optimization degree, with a regression coefficient of 0.152, that is, for each increase of 1 unit in technology application depth, the average cost structure optimization degree will increase by about 0.152. It can be seen from the above analysis that operating years, soil fertility, and farmers' education level all have a significant impact on cost management efficiency and technology implementation effect. The regression coefficient of operating years is 0.012; the regression coefficient of soil fertility is 0.087; and the regression coefficient of farmers' education years is 0.023. The regression coefficient of $TAD \times S$ is 0.001, and the coefficient value of S^2 is -0.00002. It can be concluded that the scale effect has the characteristic of marginal increase, that is, as the scale expands, the cost-saving effect brought by technology investment gradually strengthens. When the scale is close to 375 mu, the marginal benefit brought by scale expansion shows a decreasing trend. This is consistent with the theoretical expectation. In plain areas with a high level of mechanization, when the area exceeds 300 mu, mechanization replacing labor has more advantages than labor replacing labor. The interaction effect between the depth of technology application and crop type is strong, with a coefficient of 0.092 and a p-value less than 0.01, indicating that food crops have greater potential in reducing costs. The fertilizer use efficiency of food crops has increased by 23%, while that of cash crops has only increased by 8%. The fertilization operation of cash crops is complex, so the application scope of related technologies is small. This conclusion confirms the rationality of Hypothesis H3 that there is little room for cost improvement of cash crops.

4.3 Robustness Test

The cost-profit rate is used as a substitute indicator to evaluate the degree of cost structure optimization. Empirical analysis shows that the coefficient of technology application depth is 0.123, which is consistent with the benchmark model, and also proves that technology investment has a significant positive promoting effect on improving cost-effectiveness. To enhance the credibility of statistical conclusions, the core variables are subjected to 1% level winsorization to eliminate possible interference from outliers. After correction, the coefficient of technology application depth becomes 0.148, but the main conclusions of the moderating effect and mechanism test remain unchanged. This study uses "the popularity of automatic seeding and fertilization technology in the county" as an instrumental variable and conducts empirical analysis with a two-stage least squares model to solve potential endogeneity problems. The results show that the regression coefficient of technology application depth is 0.167, which well demonstrates that there is a significant causal relationship between agricultural technological innovation and the improvement of production factor costs.

5. Conclusion

After the promotion of automatic seeding and fertilization technology, the cost structure of family farms will be significantly improved. With the improvement of operation efficiency, the cost factors are redistributed. According to the research, for each increase in technology investment, the total cost decreases by an average of about 0.152 units, among which labor cost decreases by 8.7%, mechanical cost increases by 5.3%, and material cost decreases by 4.2%, accounting for 74.4% in total. The performance of this technology varies among different scales and crop types. When the farm area is larger than 300 mu, the optimization effect shows an increasing trend. In plain areas with a high level of mechanization, food crops are more economical than cash crops. The fertilizer uses efficiency of the former increases by 23%, while that of the latter only increases by 8%. The fertilization operation of cash crops is complex, so the application scope of related technologies is small. The supporting conditions for technology application have a significant impact on the cost optimization effect. The research shows that family farms with long operating years, high soil fertility, and high education levels have better cost control in technology application, which also indicates the importance of the synergistic effect of technology, management, and resources in improving economic benefits. Automatic seeding and fertilization technology provides a feasible way for family farms to implement refined cost management. In the future, it is necessary to formulate differentiated technology promotion plans according to the different scale characteristics of family farms, and strengthen the integration of technological innovation and operation management, so as to maximize the economic value of agricultural technology.

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