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Self-Owned or Outsourced? The Impact of Farm Machinery Adoption Decisions on Chinese Farm Households' Operating Income

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Abstract: Using farm machinery plays a significant role in easing the issue of slowing growth of operating income among farm households in China. Drawing data from CFPS2018, this study adopts a multinomial endogenous switching regression (MESR) to analyze the factors influencing farm households' choices regarding self-owned farm machinery and outsourced machinery services, as well as their subsequent impact on operating income. The results of the study show that the characteristics of the head of household, family, village, and region have a significant impact on the farm households' selection of whether to use self-owned machinery or outsourced services. Furthermore, the exclusive use of self-owned farm machinery and the combined use of both self-owned and outsourced machinery substantially enhance farm households' operating income. An additional analysis indicates that these two types of machinery are complementary, and their combined use generates a superimposed effect that further boosts income. These findings suggest that the combined use of self-owned and outsourced machinery is optimal for farm households who wish to expand their operating income.

Keywords: self-owned farm machinery; outsourced machinery services; operating income; superimposed effect; multinomial endogenous switching regression

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1. Introduction

With the acceleration of China's urbanization, there has been an enormous transfer of surplus rural labor force to industry and services [1–3]. This shift has led to a decline in both the quality and quantity of China's agricultural workforce [4,5], increased labor costs in farming [6,7], as well as a reduction in the efficiency and quantity of food production [8]. Meanwhile, climate risk in China is also increasing, which raises the frequency and intensity of environmental catastrophes, resulting in a decrease in farmers' operating income [9]. In terms of quantity, Chinese farm households' operational income is significantly less compared to that of Japan and South Korea, which also have a huge population on very scarce land [10]. Meanwhile, the growth rate of net operating income of Chinese farm households declined from 9.66% in 2012 to 5.47% in 2020 (Figure 1) (Data source: 2012–2020 China Rural Statistics Yearbook, available at https://www.stats.gov.cn/, accessed on 15 September 2024), which reflects the problem of a low total and slowing growth of operating income of Chinese farm households. In 2015, the United Nations Summit formally adopted 17 Sustainable Development Goals (details available at https://www.un.org/sustainabledevelopment/, accessed on 15 September 2024). Increasing operating income motivates farmers to scale up production, addresses relative poverty among some farmers, ensures global food security, and advances the achievement of the sustainable development goals of "No poverty" and "Zero hunger". Therefore, under the constraints of labor force shortage and global warming, exploring how to guarantee the sustainable growth of farm households' operating income has a significant practical relevance.

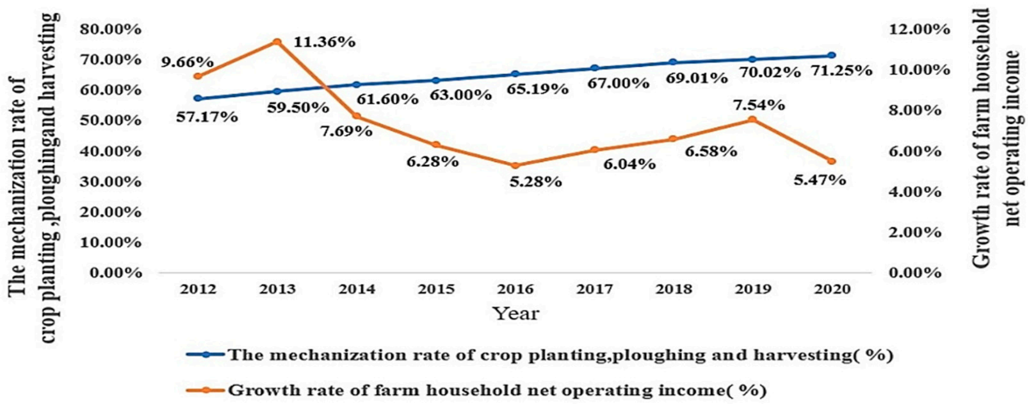

Figure 1. Trends in the comprehensive mechanization rate and growth rate of net operating income of farm households in China from 2012 to 2020.

In *Transforming Traditional Agriculture*, Schultz highlights that the introduction of new production factors is beneficial for modernizing traditional agriculture and enhancing productivity [11]. Farm machinery is a crucial technological investment in the agricultural sector [12]. Existing research identifies three key ways in which the use of agricultural machinery boosts farmers' operating income: reducing labor costs [13,14], increasing production efficiency and output [15], and mitigating the risks posed by natural disasters [16]. Driven by technological progress, increasing labor costs, and expanded government subsidies, the degree of agricultural mechanization in China has increased in recent years [17–19]. Relevant statistics reveal that China's comprehensive mechanization rate of crop planting, ploughing, and harvesting increased from 57.17% in 2012 to 71.25% in 2020 (Figure 1) (Data source: 2012–2020 China Agricultural Machinery Industry Yearbook, available at https://data.cnki.net/, accessed on 15 September 2024), contributing to an increase in farm households' operational income. However, farm households have two main options for agricultural mechanization: acquiring outsourced machinery services or directly purchasing farm machinery [5,20,21]. Therefore, a critical issue is what factors affect households' choices between purchasing farm machinery and using outsourced machinery services, and how these decisions affect their operating income. Addressing this issue will contribute to advancing the further development of agricultural mechanization in China and enhance the income-boosting benefits of farm machinery.

Due to government subsidies, both self-owned agricultural machinery and outsourced machinery services have become widely utilized in agricultural production across China. Meanwhile, the widespread use of both these types of agricultural machinery has led to a surge in related research. For instance, Baiyegunhi et al. [22] and Mi, et al. [23] have utilized models such as PSM and ESR to analyze the factors influencing farmers' choice of outsourced machinery services based on the characteristics of the household head, family, and village, noting that outsourced services contribute to increased farmers' income. Li et al. [24] analyzed the factors affecting the utilization rate of small-scale farm machinery in hilly regions. They highlighted that self-owned machinery plays a crucial role in ensuring food production in these hilly areas. Existing research has been helpful in exploring the impact of machinery adoption decisions on operating income. However, these studies often focus on single types of machinery and overlook cases where farmers use both types of farm machinery, making it necessary to include both self-owned machinery and outsourced services in a unified research framework to comprehensively examine their effects on operating income.

Based on the previous analysis, this paper uses the MESR model to study the factors influencing the adoption decisions of farm machinery and the impact of these decisions on households' income. The specific research objectives are as follows: First, employing a multinomial logit model to investigate the factors affecting households' decisions and to explore the decision-making mechanisms for two types of machinery. Second, using the MESR model to address potential selection bias and endogeneity issues, accurately measuring the impact of different types of machinery on households' operating income. Third, examining the relationship between self-owned farm machinery and outsourced machinery services, and analyzing the superimposed effects of using both types of machinery. This paper makes the following contributions: Firstly, it considers the combined use of two kinds of farm machinery and provides a comprehensive analysis of how machinery adoption affects farm households' operating income. Secondly, this paper not only examines the income disparities between utilizing farm machinery and not utilizing agricultural machinery, but also evaluates the variations in income resulting from the use of different types of farm machinery. Finally, the paper also investigates the superimposed effect of the joint utilization of two types of farm machinery.

The remaining parts of this paper are arranged in the following manner: Section 2 provides a theoretical framework; Section 3 provides an explanation of the method employed in this paper; Section 4 describes the data sources, selection of variables, descriptive statistics, and results of the mean difference test; Section 5 displays the results of the MERS model's three phase and robustness test; Section 6 further analyzes the findings of this paper; and Section 7 concludes this study, suggests related strategies, and summarizes the limitations.

2. Theoretical Framework

2.1. Factors Affecting the Adoption of Farm Machinery

Transaction cost theory suggests that market transactions and internal production within firms represent two distinct forms of labor division [25,26]. Firms incur costs associated with searching for trading partners, negotiating contracts in the market and so on, which are referred to as transaction costs. When transaction costs are low, firms are likely to opt for purchasing the required goods or services in the market. Conversely, when transaction costs are high, firms may choose to produce the goods or services internally. Similarly, we can consider farm households as small-scale agricultural enterprises. When the transaction costs of obtaining outsourced services are relatively high, farmers tend to invest in agricultural machinery and implement internal labor divisions within the household. When the transaction costs of obtaining outsourced services are relatively low, farmers opt to purchase agricultural machinery services to facilitate the market-based division of labor in production. Thus, their adoption of the two types of farm machinery is affected by transaction costs.

Williamson highlighted that transaction costs are influenced by factors such as the uncertainty and frequency of the transaction as well as the specificity of the assets involved [27]. Current research has demonstrated that farmers' agricultural machinery selection is impacted by a number of factors, including household head, household, and village characteristics, as well as regional attributes. Individual characteristics comprise age, gender, level of education, health condition, and the household head's own risk preferences [28–30]. For instance, Tufa et al. [28] investigated Malawian farmers and found that age, gender, and educational attainment had a positive influence on the adoption of outsourced machinery services. Household characteristics include factors such as household wealth, labor force, land scale, degree of land transfer, access to credit services, and social relations [31–35]. For example, Qiu et al. [31] used data from wheat farmers to demonstrate the existence of an inverted u-shaped relationship between land size and the adoption of outsourced machinery services. Village and regional characteristics mainly include factors such as distance to the nearest town, village topography, and regional economic characteristics [33,36]. For example, Zang et al. [36] noted that farmers far away from townships were more willing to adopt farm machinery outsourced services. Furthermore, Qu et al. [29] also noted that that the price and quality of outsourced machinery service delivery will influence farmers' desire to acquire farm machinery services from the supply side.

Therefore, factors such as individual, family, village, and region characteristics, as well as the quality of machinery services may reflect the transaction costs associated with acquiring outsourced services, thereby affecting farmers' choices between different types of machinery.

2.2. Impacts of Adoption of Farm Machinery on Operating Income

Technical Innovation Theory suggests that the introduction of a new factor of production enhances total factor productivity and stimulates economic growth [37]. The introduction of machinery as a new technology in farming enhances the efficiency of land and labor utilization, leading to increased output and expanded farmer incomes. Meanwhile, according to the Diffusion of Innovations Theory [38], when one farmer adopts agricultural machinery and realizes income growth, other farmers are likely to follow suit, thereby raising the level of regional agricultural mechanization and boosting the income of neighboring farmers. However, "agricultural machinery" is a broad concept. Therefore, a more nuanced analysis of farmers' machinery utilization behaviors is needed.

Adopting self-owned farm machinery reflects farmers' preference for internal labor division within their households, which helps to avoid the transaction costs of acquiring outsourced services. Due to the high capital required to purchase machinery, farmers are inclined to expand production scale as well as increase the frequency and intensity of machinery utilization. For example, Su et al. [39] noted that large-scale and specialized farmers benefit more from the use of their self-owned farm machinery, while small-scale farmers benefit more from the use of outsourced farm machinery services. Meanwhile, farm households' adoption of self-owned machinery indicates their independent efforts to modernize agricultural production. Self-owned machinery is typically used for several years. Based on the theory of "Learning by Doing" [40], farmers become increasingly adept at using machinery, accumulating production experience in modern agriculture, which continuously boosts productivity and expands their operating income.

The adoption of outsourced machinery services fundamentally reflects an idea of specialized division of labor [41–43]. Yet Smith noted the limited scope for specialization in agricultural production and argued that it is not suited for outsourcing [44]. However, with the expansion of government subsidies and market demand, the market supply of outsourced services has continually increased, leading to a reduction in transaction costs for obtaining services. This has prompted farmers to outsource the labor-intensive parts of the agricultural chain to specialized organizations [31,41,45], realizing the replacement of scarce labor with relatively inexpensive farm machinery services, saving labor costs [46,47], and enhancing operating income. Based on the above analysis, the following hypothesis is proposed:

H1. *Using self-owned farm machinery increases the farm household's operating income.*

H2. *Using outsourced farm machinery services increases the farm household's operating income.*

2.3. Relationship between Self-Owned Farm Machinery and Outsourced Farm Machinery Services

Existing research lacks a consensus on the relationship between both these types of farm machinery. Su et al. [39] suggest that self-owned machinery and outsourced services represent two alternative mechanization strategies. In contrast, Qian et al. [5] argue that both types of farm machinery differ in application segments and exhibit a complementary relationship. To investigate the relationship between the two types of agricultural machinery, it is essential to compare the strengths of their substitution effects and complementary effects. Some studies indicate that self-owned machinery is better suited for large-scale farming operations [31] and is primarily used in field management activities such as fertilization and pest control. In contrast, outsourced machinery services are more suitable for small-scale farmers and are often used in labor-intensive tasks like plowing and harvesting. Therefore, the two types of farm machinery serve different production scenarios and are more complementary than substitutes. Meanwhile, some survey data support this conjecture. According to the "China Family Farm Development Report" (available at https://www.sklib.cn/, accessed on 15 September 2024), the average value of agricultural machinery owned by sample farms was 221.3 thousand RMB in 2016, rising to 250.5 thousand RMB in 2018. In 2016, 47.73% of family farms did not purchase outsourced services, whereas this proportion decreased to 42.27% in 2018. These data suggest that the sample farms may have expanded the use of both types of farm machinery, reflecting a possible complementary relationship between the two types of farm machinery. Moreover, according to risk diversification theory, the joint use of both types of machinery helps mitigate operational risks and leverages the additive effects of each type. Based on the above analysis, the following hypothesis is proposed:

H3. *In the current agricultural production in China, the two types of farm machinery are complementary.*

3. Methods

Farmers' adoption of farm machinery is not strictly exogenous, but it is affected by both observable factors (number of family members engaged in agricultural and non-agricultural employment, land scale, etc.) and unobservable factors (farmers' expectations of operating income, etc.), and unobservable factors may affect both the decision regarding farm machinery selection and the farmers' operating income, resulting in a sample self-selection problem and endogeneity problem. The failure to address the selection bias caused by both observable and unobservable heterogeneity will lead to erroneous estimation results [48,49].

Common methods for solving self-selection and endogeneity problems include the propensity score matching (PSM), difference in differences model (DID), and endogenous switching regression model (ERS) [50,51]. PSM is commonly employed in evaluating the impacts of policies or technologies. It effectively addresses the selection bias arising from observable variables but struggles to correct for biases introduced by unobservable factors. [52,53]. DID is more widely used in the assessment of policy effects, which can effectively control temporal variations of the study sample and measure the impact of policy implementation [54]. However, DID requires panel data collected before and after policy implementation, making it challenging to apply to cross-sectional data [50,55]. ESR is extensively used to address sample bias and endogeneity issues [56]. It can simultaneously address the selection bias caused by both observable and unobservable variables, but it only applies to cases where the study samples are categorized into two types [51,57].

Given that this study utilizes cross-sectional data and categorizes farm households into four (2^2) groups based on their adoption of self-owned farm machinery and outsourced machinery services, the DID and ESR models are not applicable. Considering that PSM struggles to correct the selection bias caused by unobservable variables, referring to similar studies [50,51,55], this paper has chosen the MESR model to deal with the selection bias caused by observable and unobservable variables.

The MERS model has three phases. The first phase utilizes a multinomial logit selection model to estimate households' adoption of farm machinery. The second phase uses OLS, which introduces inverse mills ratios to examine the influence of a group of exogenous factors on farm households' operating income under different choices. And the third phase estimates the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU).

3.1. First Phase—Multinomial Selection Logit Model

In the first phase, this paper uses a multinomial logit selection (MNLS) model to estimate the farm households' selection equation for farm machinery. In this paper, farm households are faced with four mutually exclusive choices: non-use of farm machinery

(Non-use); only using self-owned farm machinery (OFM); only using outsourced machinery services (OMS); and the joint use of both types of agricultural machinery (Both-use). The farm households' adoption decisions follow the random utility theory [48]; assuming that the farm households are rational economic agents, they will evaluate the anticipated benefits of using different types of farm machinery and make the adoption decision that maximizes expected utility. Specifically, a farm household's assessment of the utility of using farm machinery can be expressed in the following equation:

$$U_{ij}^{*} = \beta_j X_{ij} + \varepsilon_{ij} \tag{1}$$

The latent variable U_{ij}^{*} denotes the level of utility of farm households under different choices of farm machinery, influenced by both observable and unobservable factors. X_{ij} denotes a group of observable factors, including household head, household, and village characteristics, as well as regional attributes. ε_{ij} is the random error term, denoting unobservable factors (the farm household's risk appetite, etc.) β_j is the estimated coefficient of X_{ij}.

The utility derived from the use of farm machinery by households is hard to observe directly, but the adoption behavior of households towards farm machinery is observable. Specifically, the equation representing farm households' choice of machinery can be expressed as follows:

$$A_i = \begin{cases} 1, & if \quad U_{i1}^{*} > \underset{k \neq 1}{max}\left(U_{ik}^{*}\right) \; or \; \pi_{i1} < 0 \\ \vdots & \\ j, & if \quad U_{ij}^{*} > \underset{k \neq j}{max}\left(U_{ik}^{*}\right) \; or \; \pi_{ij} < 0 \end{cases} \tag{2}$$

A_i denotes the index that indicates the households' selection of farm machinery (1 = Non-use, 2 = OFM, 3 = OMS, 4 = Both-use). Where $\pi_{ij} = \underset{k \neq j}{max}\left(U_{ik}^{*} - U_{ij}^{*}\right) < 0$, indicating household i will adopt farm machinery j (j = 1, …, 4) if U_{ij}^{*} of using the machinery j is greater than that of any other machinery k ($k \neq j$).

Given the assumption that ε_{ij} is identically and independently Gumbel-distributed [58], the probability that farm household i with characteristic X_{ij} will adopt farm machinery j can be represented by the following multinomial logit model [59]:

$$P_{ij} = Pr\left(U_{ij}^{*} > \underset{k \neq j}{max}\left(U_{ik}^{*}\right) \middle| X_i\right) = \frac{\exp\left(\beta_j X_{ij}\right)}{\sum_{j=1}^{j} \exp\left(\beta_j X_{ij}\right)} \tag{3}$$

3.2. Second Phase—Estimation of Outcome Equation

The MESR model's second phase will estimate the impact of adopting diverse machinery (1 = Non-use, 2 = OFM, 3 = OMS, 4 = Both-use) on the households' operating income by constructing the following income-determining equation:

$$\begin{cases} Regime1 : Y_{i1} = \alpha_1 Z_{i1} + \mu_{i1}, & if \; A_i = 1 \\ \vdots & \\ Regimej : Y_{ij} = \alpha_j Z_{ij} + \mu_{ij}, & if \; A_i = j \end{cases} \tag{4}$$

Here, Y_i denotes the operating income of farm household i in Regime 1 to j. Z_{ij} is a group of exogenous factors affecting the operating income of farm household i who adopts machinery j, including the individual, household, village, and regional characteristics. α_j is the estimated coefficient of Z_{ij}. The random error term μ_i satisfies the condition that $\mathrm{E}(\mu_i | X, Z) = 0$, $\mathrm{var}(\mu_i \mid X, Z) = \sigma_j^2$.

In Equation (4), a group of observable variables that may affect the farm households' operating income is introduced, which helps address the selection bias arising from these observable variables [60]. However, if some unobservable factors simultaneously affect both A_i in Equation (2) and Y_i in Equation (4), it implies that the error terms in the outcome Equation (4) and the selection Equation (2) are correlated. In this case, applying a simple OLS regression to Equation (4) would result in biased and inconsistent estimates of α_i [61]. To correct the potential selection bias due to unobservable variables, following Bourguignon et al. [58], a selection correction term for different farm machinery choices can be introduced into Equation (4) to achieve an unbiased and consistent estimate of α_i. Therefore, Equation (4) can be corrected as follows:

$$\begin{cases} Regime1: Y_{i1} = \alpha_1 Z_{i1} + \sigma_1 \hat{\lambda}_{i1} + \theta_{i1}, \quad if\ A_i = 1 \\ \vdots \\ Regimej: Y_{ij} = \alpha_j Z_{ij} + \sigma_j \hat{\lambda}_{ij} + \theta_{ij}, \qquad if\ A_i = j \end{cases} \tag{5}$$

where σ_i is the covariance of the random error terms μ_i in Equation (4) and ε_i in Equation (1). The Inverse Mills Ratio $\hat{\lambda}_{ij} = \sum_{k \neq j}^{j} \rho_j \left[\frac{\hat{\rho}_{ki} ln(\hat{\rho}_{ki})}{1-\hat{\rho}_{ki}} + ln(\hat{\rho}_{ij}) \right]$, which is derived from the estimation of Equation (3). ρ_i represents the correlation coefficient of μ_i and ε_i. θ_i is the random error term with an expected value of 0. Meanwhile, in order to identify the MERS model effectively, it is necessary to ensure that at least one of the explanatory variables in the selection Equation (1) is not included in the outcome Equation (5), which directly affects the choice of machinery of the farm household without directly affecting their income [62–64].

3.3. Third Phase—Estimation of ATT and ATU

The third phase of the MESR assesses the impact of choosing different farm machinery by comparing the farm household expected operating income in factual and counterfactual situations and estimating the average treatment effect for the control group (non-adopters: j = 1) and treatment group (adopters: including OFM, OMS and Both-use groups, j = 2, 3, 4).

Adopters with adoption (factual situation):

$$E\left(y_{ij} \mid U = j, Z_{ij}, \hat{\lambda}_{ij}\right) = \alpha_j Z_{ij} + \sigma_j \hat{\lambda}_{ij} \tag{6}$$

Adopters had made the decision not to adopt (counterfactual situation):

$$E\left(y_{i1} \mid U = j, Z_{ij}, \hat{\lambda}_{ij}\right) = \alpha_1 Z_{ij} + \sigma_1 \hat{\lambda}_{ij} \tag{7}$$

Non-adopters with non-adoption (factual situation):

$$E\left(y_{i1} \mid U = 1, Z_{i1}, \hat{\lambda}_{i1}\right) = \alpha_1 Z_{i1} + \sigma_1 \hat{\lambda}_{i1} \tag{8}$$

Non-adopters had made the decision to adopt (counterfactual situation):

$$E\left(y_{ij} \mid U = 1, Z_{i1}, \hat{\lambda}_{i1}\right) = \alpha_j Z_{i1} + \sigma_j \hat{\lambda}_{i1} \tag{9}$$

To obtain an unbiased estimate of the average treatment effect on the treated group (ATT), we can calculate the difference between Equations (6) and (7):

$$\begin{aligned} \text{ATT} \quad &= E\left(y_{ij} \mid U = j, Z_{ij}, \hat{\lambda}_{ij}\right) - E\left(y_{i1} \mid U = j, Z_{ij}, \hat{\lambda}_{ij}\right) \\ &= Z_{ij}\left(\alpha_j - \alpha_1\right) + \hat{\lambda}_{ij}\left(\sigma_j - \sigma_1\right) \end{aligned} \tag{10}$$

To obtain an unbiased estimate of the average treatment effect on the untreated group (ATU), we can calculate the difference between Equations (8) and (9):

$$\begin{aligned} \text{ATU} \quad &= E\left(y_{ij} \mid U = 1, Z_{i1}, \hat{\lambda}_{i1}\right) - E\left(y_{i1} \mid U = 1, Z_{i1}, \hat{\lambda}_{i1}\right) \\ &= Z_{i1}\left(\alpha_j - \alpha_1\right) + \hat{\lambda}_{i1}\left(\sigma_j - \sigma_1\right) \end{aligned} \tag{11}$$

Following Parvathi et al. [65], within the treatment group, we can further set up the control and treatment group to estimate the average treatment effect. For example, we can consider farm households using their self-owned farm machinery (OFM) as the control group $(j = 2)$ and farm households using outsourced machinery services (OMS) as the treatment group ($j = 3$).

OMS adopters remain OMS (factual situation):

$$E\left(y_{i3} \mid U = 3, Z_{i3}, \hat{\lambda}_{i3}\right) = \alpha_3 Z_{i3} + \sigma_3 \hat{\lambda}_{i3} \tag{12}$$

OMS adopters had made the decision to adopt OFM (counterfactual situation):

$$E\left(y_{i2} \mid U = 3, Z_{i3}, \hat{\lambda}_{i3}\right) = \alpha_2 Z_{i3} + \sigma_2 \hat{\lambda}_{i3} \tag{13}$$

To obtain an unbiased estimate of the average treatment effect, we can calculate the difference between Equations (12) and (13):

$$\begin{aligned} \text{ATT} &= E\left(y_{i3} \mid U = 3, Z_{i3}, \hat{\lambda}_{i3}\right) - E\left(y_{i2} \mid U = 3, Z_{i3}, \hat{\lambda}_{i3}\right) \\ &= Z_{i3}(\alpha_3 - \alpha_2) + \hat{\lambda}_{i3}(\sigma_3 - \sigma_2) \end{aligned} \tag{14}$$

4. Materials

4.1. Data Sources

The data used in this paper come from the China Family Panel Survey (CFPS) conducted by Peking University (available at https://opendata.pku.edu.cn/, accessed on 15 September 2024), which covers 25 provinces, municipalities, and autonomous regions, and includes data at the individual, household, and community levels, thus providing data with a large sample size and high statistical reliability.

The dependent variable, independent variables, and some of the control variables in this paper were obtained from CFPS2018, but due to the lack of data on village topography, distance to the nearest town, types of planted crops, and household land scale in CFPS2018, following Qian et al. [5], this paper first merged CFPS2018 with CFPS2014 to obtain data on the village topography, distance to the nearest town, and types of planted crops from CFPS2014, and further combined the newly merged data with CFPS2012 to obtain data on the land scale of farm households from CFPS2012, retaining the data of the farm households that participated in the three surveys. After deleting the missing values, 3304 valid samples were obtained.

4.2. Variable Selection

4.2.1. Dependent Variable

Operating income is the dependent variable of this study, which is defined as the income obtained by farm households from agricultural operations. Reference was made to existing studies [15,66–68]. This paper uses the CFPS2018 question "In the past 12 months, for how much did your household sell the crops, forest products, poultry, and by-products, etc. that you produced on your own?" as the measurement indicator. However, the presence of a large number of zeros in the data for this indicator may impact the accuracy of the model estimation. This paper uses the CFPS 2018 question "In the last 12 months, what was the market value of the portion of all the agricultural and forestry products, poultry, and by-products produced by your household that was eaten or used by you?" as a complementary indicator. Burke et al. [69] note that farmers will sell some or all of their produce on the market, which will be affected by market prices. So, the two indicators above reflect the actual and potential operating income of farmers, respectively. Therefore, this paper sums up the value of agricultural products that farmers put into the market and consume by themselves, in order to comprehensively reflect the operating income of farmers.

4.2.2. Independent Variables

The independent variables in this paper are dummy variables for farm households' adoption of farm machinery. Following Qian et al. [5], Deng et al. [43], and Paudel et al. [70], this article uses the CFPS2018 questions "In the past 12 months, how much did you pay for renting machinery used in agricultural production?" and "What is the overall current worth of the farm machinery under your household's ownership, not including those rented or borrowed?" as measurement indicators.

Then, the data were characterized as follows. If the rental fee is 0, i.e., outsourced machinery services were not used, it was assigned a value of 0; otherwise, it was assigned a value of 1. If the total value of the household's farm machinery is 0, i.e., self-owned farm machinery was not used, it was assigned a value of 0; otherwise, it was assigned a value of 1. Based on the four possible combinations of exclusionary choices, farm households were categorized into four groups: non-use of farm machinery (Non-use); only using self-owned farm machinery (OFM); only purchasing outsourced machinery services (OMS); and joint use of both two types of machinery (Both-use).

4.2.3. Control Variables

Considering the needs of this paper and the insights from the existing literature [5,28–36,71–73], this paper selected control variables on four aspects: household head, household, village, and regional characteristics.

Household head characteristics mainly include health status, age, gender, educational level, as well as internet usage. Health status, age, and gender reflect the capacity and desire of household heads to participate in agricultural production. The education level and internet usage represent the household head's cognitive level and willingness to absorb new experiences.

Household characteristics include land scale, land renting-in, land renting-out, agricultural labor force, off-farm employment, borrowing, government grants, expenses of seeds, etc., social networks, and types of planted crops. Land scale, land renting-in and renting-out, agricultural labor force and off-farm employment, and cost of seeds, fertilizers, and pesticides reflect the inputs of the production factors of farm households, which directly affect their operating income. Borrowing and government grants reflect the inflow of money from outside. Social networks reflect the interpersonal situation of farm households. The types of planted crops reflect the diversity of agricultural production.

Village characteristics mainly include village topography and the distance to the nearest town. Topography directly affects the efficiency of using farm machinery, while distance is a reflection of the transaction costs of farm households in acquiring machinery. Region characteristics are introduced because the regional economic development status may affect farm households' adoption of farm machinery.

4.2.4. Instrumental Variable

When estimating the MERS model, it is essential to introduce an instrumental variable. This variable is required to directly influence the selection equation but has no effect on the outcome equation. Reference was made to the existing literature [74–76]. In this paper, the proportion of farm machinery adopted in the same village except for the household was selected as the identifying variable. Farm households may imitate the behavior of other farmers and adopt the same farm machinery. However, the adoption of farm machinery by other farmers does not immediately affect the operating income of the sample farm households.

4.3. Descriptive Statistics

Table 1 shows the utilization of farm machinery by the sample farm households. Among the 3304 samples: 25.76% of the farm households did not use farm machinery (Non-use); 26.48% of the farm households only used their self-owned farm machinery (OFM);

26.97% of the farm households only used outsourced farm machinery services (OMS); and 20.79% of the farm households jointly used both types of farm machinery (Both-use).

Table 1. Farm households' adoption of two types of farm machinery.

Adoption	Frequency	Percentage (%)	Cumulative Percentage (%)
Non-use	851	25.76	25.76
OFM	875	26.48	52.24
OMS	891	26.97	79.21
Both-use	687	20.79	100.00
Total	3304	100.00	

Data source: authors' own calculations based on CFPS2018.

Table 2 contains the definitions of the variables used in this study, and the descriptive statistical results. We mainly focused on the characteristics of labor and land. The average age of the household head was 53.4. The proportion of male household heads was 57.4%. The average education level is junior and senior high-school level, and the internet usage rate was 31.8%, which indicates that the education level of the household head and the proportion of access to information technology are still relatively low. The average land area of the farm households was 11.057 mu, and the rates of land transfer in and out were 16.0% and 11.5%, respectively, which shows that most of the farm households in China operate on a small scale, and the market for land transfer in rural areas has yet to be perfected. The average value of agricultural labor force input was 2.094, and the average number of people migrating to work was 0.831, but most of the migrating labor force were young people, while most of the people engaged in agriculture were old people [77].

Table 2. Summary statistics and definition of variables.

Variable Type	Variable Name	Variable Definition	Mean	S.D.
Dependent Variable	Operating Income	Market value of crops and other produce cultivated by the family in the past 12 months (RMB, logarithm)	8.537	1.875
Independent variables	Self-owned farm machinery	Whether the farm household has self-owned farm machinery (Yes = 1, No = 0)	0.473	0.499
	Outsourced machinery services	Whether the farm household purchases outsourced machinery services (Yes = 1, No = 0)	0.478	0.500
Individual Characteristics	Age	Age of household head	53.400	11.837
	Gender	Gender of household head (male = 1; female = 0)	0.574	0.495
	Education level	Educational level of household head (illiterate = 1, primary school = 2, junior high school = 3, high school = 4, college and above = 5)	2.203	1.029
	Health	Health status of household head (very healthy = 5; healthy = 4; relatively healthy = 3; not very healthy = 2; unhealthy = 1)	2.787	1.284
	Internet	Whether to use the internet (Yes = 1; No = 0)	0.318	0.466

Table 2. *Cont.*

Variable Type	Variable Name	Variable Definition	Mean	S.D.
Family Characteristics	Land scale	Total land scale of the family in 2012 (mu)	11.057	34.149
	Land renting-in	Whether there is land renting-in for the household (Yes = 1, No = 0)	0.160	0.367
	Land renting-out	Whether there is land renting-out for the household (Yes = 1, No = 0)	0.115	0.319
	Agricultural labor force	Agricultural labor inputs	2.094	1.020
	Off-farm employment	Number of migrant workers in the family	0.831	0.977
	Loan	Whether the family owes money to friends (Yes = 1, No = 0)	0.169	0.375
	Grant	Whether the family receives government grants (Yes = 1, No = 0)	0.710	0.454
	Cost	Cost of purchasing seeds, pesticides, and fertilizers (RMB, logarithm)	7.670	1.288
	Social network	Expenses on gifts to friends (RMB, logarithm)	7.183	2.294
	Types	Types of planted crops (Including eight types: Rice, wheat, corn, soybean, peanut, potato, rapeseed and others)	2.542	1.441
Village Characteristics	Topography	The topography of the village (plain = 1, hills = 2 plateau = 3)	1.782	0.792
	Distance	Distance from the village to the nearest town (km)	4.318	4.298
Regional Characteristics	Region	The western region = 1, the central region = 2, the eastern region = 3	2.015	0.863
Instrumental variable	Proportion	Proportion of agricultural machinery adopted in the same village except for the household	0.739	0.246

Data source: authors' own calculations based on CFPS 2012, CFPS 2014 and CFPS 2018.

4.4. Mean Difference Test of Variables

Following Amankwah et al. [78], this paper further presents the results of mean difference tests categorized by the adoption in Table 3. Firstly, we found that farm households using farm machinery had a higher income than those not using farm machinery, and that there were significant differences between them in terms of the household head, family, village, and region characteristics. Secondly, farm households that jointly use two types of farm machinery had the highest income, which may be related to higher education levels, land scale, agricultural labor force, as well as higher costs for seeds, pesticides, and fertilizers Finally, we also observed an interesting phenomenon that there seems to be an inverse choice in the allocation of the labor force between farm households using their own farm machinery and those using outsourced machinery services, the former having a higher agricultural labor force input, the latter have higher non-farm labor force inputs. This indicates that use of different kinds of agricultural machinery may have different impacts on the distribution of labor between the agricultural and non-agricultural industries.

Table 3. Mean difference test of variables.

Variable Name	Non-Use	OFM	OMS	Both-Use
Operating Income	7.857	8.823 ***	8.409 ***	9.179 ***
Age	54.395	51.090 ***	55.418 *	52.492 ***
Gender	0.545	0.633 ***	0.517	0.606 **
Education level	2.074	2.145	2.213 ***	2.422 ***
Health	2.841	2.783	2.675 ***	2.869
Internet	0.251	0.368 ***	0.292 *	0.371 ***
Land scale	8.885	16.254 ***	7.901	11.223 **
Land renting-in	0.081	0.193 ***	0.147 ***	0.233 ***
Land renting-out	0.130	0.096 **	0.130	0.102 *
Agricultural labor force	1.947	2.358 ***	1.934	2.146 ***
Off-farm employment	0.743	0.749	0.914 ***	0.936 ***
Loan	0.152	0.185 *	0.165	0.175
Grant	0.624	0.714 ***	0.735 ***	0.779 ***
Cost	7.141	7.936 ***	7.586 ***	8.098 ***
Social network	6.730	7.360 ***	7.238 ***	7.450 ***
Types	2.465	2.937 ***	2.336 *	2.402
Topography	1.984	2.163 ***	1.473 ***	1.447 ***
Distance	4.773	5.104	3.699 ***	3.556 ***
Region	2.069	1.709 ***	2.203 ***	2.092
Proportion	0.567	0.724 ***	0.810 ***	0.878 ***
Number of observations	851	875	891	687

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$. Data source: authors' own calculations based on CFPS2012, CFPS 2014, and CFPS 2018.

5. Results

5.1. Results of Multinomial Logit Selection Model

Farm households that do not use agricultural machinery were designated as the reference group. Table 4 displays the estimated coefficients and marginal effects of the MNLS model. The outcome of the Wald test ($\chi^2(57)$ = 1155.52; $p = 0.000$) is significant at a 1% level, indicating that the model fit is relatively good [79]. Since it is more convenient to explain individual probability by marginal effect [80], this paper analyzes the results accordingly based on the marginal effect.

In terms of household head characteristics, firstly, male household heads who are younger and have lower levels of education are more inclined to adopt self-owned farm machinery. A low level of education can limit household heads' opportunities for off-farm employment, leading them to focus on agricultural production. Younger male family heads possess greater proficiency in using self-owned farm machinery. Secondly, older and less healthy female household heads who have access to the internet are more inclined to utilize outsourced machinery services. Unhealthy female farm household heads have difficulty in engaging in agricultural production and need to be replaced by farm machinery. Access to the internet reduces the transaction costs associated with purchasing outsourced machinery services, making them a more attractive option. Thirdly, male household heads with a higher education level are more likely to jointly use two types of farm machinery. Higher education may encourage farm households to evaluate the advantages and disadvantages of each type of farm machinery and apply them to the most suitable aspects of agricultural production.

In terms of household characteristics, land scale, agricultural labor force input, off-farm employment, cost of seeds, etc., and the type of crop operated significantly affect the adoption of farm machinery. However, the impacts are opposite for farm families that adopt self-owned farm machinery and those that rely on outsourced machinery services. The former has a positive benefit, while the latter experience a negative effect. This difference may stem from the distinct characteristics of these two types of agricultural machinery.

Table 4. Multinomial logit model estimates of adoption of agricultural machinery.

Variable	OFM		OMS		Both-Use	
	Coef.	Marginal Effect	Coef.	Marginal Effect	Coef.	Marginal Effect
Age	−0.001 (0.005)	−0.001 ** (0.001)	0.020 *** (0.006)	0.003 *** (0.001)	0.005 (0.006)	−0.001 (0.001)
Gender	0.252 ** (0.114)	0.031 ** (0.015)	−0.047 (0.114)	−0.039 ** (0.015)	0.265 ** (0.129)	0.029 ** (0.014
Education level	0.002 (0.058)	−0.013 * (0.008)	0.092 (0.058)	0.003 (0.008)	0.189 *** (0.064)	0.020 *** (0.006)
Health	−0.049 (0.042)	−0.001 (0.006)	−0.099 ** (0.043)	−0.012 ** (0.006)	−0.040 (0.048)	0.003 (0.005)
Internet	0.445 *** (0.138)	0.040 (0.018)	0.309 ** (0.143)	0.006 ** (0.018)	0.365 ** (0.155)	0.010 (0.016)
Land scale	0.003 * (0.002)	0.001 ** (0.000)	−0.007 (0.005)	−0.002 ** (0.001)	0.004 * (0.002)	0.001 *** (0.000)
Land renting-in	0.577 *** (0.169)	0.017 (0.020)	0.635 *** (0.176)	0.018 (0.021)	0.943 *** (0.182)	0.063 *** (0.017)
Land renting-out	−0.156 (0.173)	−0.013 (0.023)	−0.087 (0.164)	0.004 (0.023)	−0.162 (0.192)	−0.010 (0.021)
Agricultural labor force	0.259 *** (0.053)	0.040 *** (0.007)	−0.037 (0.061)	−0.027 *** (0.008)	0.104 (0.065)	0.005 (0.007)
Off-farm employment	−0.044 (0.058)	−0.027 *** (0.008)	0.210 *** (0.057)	0.026 *** (0.007)	0.193 *** (0.064)	0.015 ** (0.007)
Loan	−0.056 (0.146)	−0.008 (0.019)	0.006 (0.150)	0.006 (0.020)	−0.032 (0.165)	−0.002 (0.018)
Grant	0.072 (0.117)	−0.018 (0.016)	0.315 *** (0.119)	0.032 * (0.017)	0.294 ** (0.137)	0.017 (0.016)
Cost	0.387 *** (0.049)	0.043 *** (0.007)	0.056 (0.046)	−0.034 *** (0.007)	0.354 *** (0.056)	0.028 *** (0.006)
Social Network	0.061 *** (0.023)	0.001 (0.003)	0.090 *** (0.024)	0.006 * (0.004)	0.092 *** (0.028)	0.004 (0.003)
Types	0.218 *** (0.037)	0.030 *** (0.005)	0.031 (0.040)	−0.011 ** (0.007)	0.075 (0.046)	−0.002 (0.005)
Topography	0.284 *** (0.079)	0.010 *** (0.010)	−0.574 *** (0.083)	−0.083 *** (0.012)	−0.477 *** (0.095)	−0.042 *** (0.011)
Distance	0.002 (0.012)	0.003 * (0.002)	−0.017 (0.014)	−0.001 (0.002)	−0.034 ** (0.016)	−0.004 * (0.002)
Region	−0.134 * (0.071)	−0.035 *** (0.010)	0.150 ** (0.072)	0.025 *** (0.010)	0.116 (0.081)	0.012 (0.009)
Proportion	2.292 *** (0.228)		3.742 *** (0.251)		6.118 *** (0.362)	
Constant	−6.503 *** (0.686)		−4.344 *** (0.687)		−9.265 *** (0.841)	
Wald test: $\chi^2(57)$	1155.52 ***					
Sign. of instrument	380.46 ***					
Number of observations	3304					

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$. Robust standard errors are presented in parentheses. "Non-use" was the reference category.

Firstly, in terms of cost, purchasing self-owned agricultural machinery is typically more expensive than outsourced machinery services and involves additional maintenance and repair costs, resulting in a higher investment threshold. Secondly, in terms of ownership, self-owned farm machinery offers asset exclusivity, granting farmers complete control over its use. This allows farmers to manage the timing and frequency of usage according to their production schedules. However, as a privately-owned asset, it also incurs depreciation and maintenance costs, with the added risk of equipment idleness. In contrast, outsourced machinery services entail asset sharing, where farmers only hold temporary usage rights. This arrangement avoids maintenance and depreciation costs and is often well-suited for seasonal or temporary production needs. Nevertheless, during peak demand periods, there may be competition, potentially leading to delays in accessing required services. Finally, in terms of human capital requirements, self-owned farm machinery needs to be used in conjunction with labor forces that have the skills to operate the machinery, whereas outsourced machinery services do not have this requirement, replacing labor and only requiring farm households to supervise the quality of the services.

Large-scale farm households have more production factor inputs, such as labor force and land, which reduces the unit cost of purchasing farm machinery. Meanwhile, to leverage scale effects, they use farm machinery more frequently and intensively, emphasizing that agricultural machinery can be put into production in a timely manner, hence purchasing agricultural machinery is more cost-effective than frequently hiring external services. However, smaller farm households struggle with the cost of purchasing machinery, while outsourced services substitute for labor and made up for their lack of labor force. Meanwhile, a greater diversity of crops managed indicates a stronger willingness regarding agricultural production and reflects the farmers' extensive experience and capability in handling various agricultural tasks. Such farmers are more likely to implement labor division within their households, avoiding the transaction costs associated with outsourcing agricultural machinery services, which in turn encourages the use of their own agricultural machinery. Therefore, the different scales of production have led to the adoption of different characteristics of agricultural machinery by farm households. Specifically, in terms of labor input in agriculture, the increase in labor input has promoted the adoption of self-owned farm machinery and reduced reliance on outsourced services, which shows that self-owned farm machinery and labor force complement each other, while outsourced machinery services replace labor force. These findings correspond with the research conducted by Qian et al. [5]. Meanwhile, land scale, land transfer, non-agricultural employment, and costs for seeds, etc., significantly positively impact the joint use of both types of agricultural machinery.

Village characteristics, including topography and the distance to the nearest town, significantly influence farm households' adoption of farm machinery. Farm households in hilly and plateau regions are more inclined to use self-owned machinery, whereas those in plain areas tend to rely on outsourced machinery services. This is likely because self-owned farm machinery is mostly small-scale, while the farm machinery that provides services is usually large-scale. In hilly and plateau areas, land is fragmented and the terrain is undulating, making it more suitable for small-scale farm machinery [33,70]. In plain areas, farmland is contiguous and the terrain is flat, making it more suitable for large-scale farm machinery. The negative impact of topography on farm households who jointly use two types of machinery is less significant compared to those using only outsourced services, indicating that the joint use of two types of machinery benefits households operating in diverse terrains. The distance to the nearest town positively affects the use of self-owned farm machinery but negatively impacts the joint use of both types of machinery. The reason may be that the further away from the town they are, the more difficulty farmers have in obtaining the necessary farm machinery services. To ensure timely production, farm households are compelled to purchase self-owned machinery. Farm households that are closer to the town may have higher incomes and be more able to pay for farm machinery. Additionally, the supply of farm machinery and farm machinery services is more comprehensive, and farm households have the opportunity to jointly use two types of farm machinery to meet their diverse operational requirements.

Regional characteristics significantly influence farm households' adoption of farm machinery. Farm households in the western region are more inclined to use self-owned agricultural machinery, whereas those in the eastern region prefer outsourced machinery services. One possible reason for this is that the outsourced machinery services system in eastern China is more complete than in the west [41], which influences farm households' options.

Regarding the validity of the tool variable, it is significant in the selection equation (χ^2 = 370.02; $p = 0.000$). Meanwhile, Table A1 reports the outcomes of the unidentifiable test and weak instrument test. The outcome of the under-identification test is significant at the 1% level, leading to the rejection of the null hypothesis. Additionally, the weak instrument test statistic is 571.336, which surpasses the critical value of 10 [81], suggesting that the weak instrument issue is not present.

5.2. Analysis of the Average Treatment Effect

Since the regression results of the second phase of the MESR are not very important, some studies [64,78] do not report these results in the main text but instead include them in the Appendix A. Therefore, this paper mainly reports the results of the third phase of the MESR in this section, and the results of the second phase of the MERS are presented in Table A2. Some inverse mills ratios (λ_i) in Table A2 are statistically significant, representing the existence of self-selection problems, so it is necessary to use the MERS model.

Since the logarithmic value of operating income lacks a specific unit and only measures the relative size of income among different households, it cannot reflect the real values of income and lacks practical significance. Referring to Pan et al. [50], to estimate ATT and ATU, this study performed a mean difference test on the antilogarithm of the predicted operating income(log) of households between the actual and counterfactual situation, and the outcomes are displayed in Tables 5–9.

Table 5. The results of the average treatment effects of the treated group (ATT).

Variable	Actual Selection	Counterfactual Selection	Actual Income (1)	Counterfactual Income (2)	ATT (3) = (1)−(2)	Change (%) (4) = (3)/(2)
Operating income	OFM	Non-use	9230.364 (316.835)	7856.208 (333.455)	1374.156 *** (282.337)	17.491%
	OMS		5644.804 (140.283)	5541.018 (211.292)	103.786 (156.909)	1.873%
	Both-use		12,815.696 (467.332)	9821.862 (495.780)	2993.834 *** (442.500)	30.481%

Note: *** denote $p < 0.01$. Robust standard errors are presented in parentheses.

Table 6. The results of the average treatment effects of the untreated group (ATU).

Variable	Actual Selection	Counterfactual Selection	Actual Income (1)	Counterfactual Income (2)	ATT (3) = (2)−(1)	Change (%) (4) = (3)/(1)
Operating income	Non-use	OFM	3709.081 (132.996)	5331.927 (237.524)	1622.846 *** (181.867)	43.753%
		OMS		4706.465 (165.034)	997.384 *** (106.922)	21.192%
		Both-use		6302.024 (290.513)	2592.943 *** (213.099)	69.908%

Note: *** denote $p < 0.01$. Robust standard errors are presented in parentheses.

Table 5 displays the average treatment effects of adopting farm machinery on the operating income of the treatment group. The results in Table 5 reveal that farm households with a joint adoption of both kinds of farm machinery had the highest operating income of RMB 12,815.696, followed by those who used only self-owned farm machinery with RMB 9230.364, and lastly, those who used only outsourced farm machinery services with RMB 5644.804. The outcomes of ATT indicate that the use of self-owned farm machinery and the joint use of both kinds of agricultural machinery significantly increase farm households' operating income. Thus, H2 was validated. Correspondingly, the data in column (4) show that if these two types of farm households do not use farm machinery, their operating income will decrease by 17.491% and 30.481%, respectively. However, only using outsourced machinery services did not significantly increase the operating income of farm households. This seems to be contrary to the results of existing studies [23,72]. The data in Table 3 show that farm households that only use outsourced machinery services are the smallest in terms of agricultural labor force input and land scale. Fewer agricultural factor inputs may weaken the income-generating effects of outsourced machinery services. Finally, this paper visualizes the data of Table 5, which are shown in Figure A1.

Table 7. The results of the average treatment effects.

Variable	Actual Selection	Counterfactual Selection	Actual Income (1)	Counterfactual Income (2)	ATT (3)=(1)−(2)	Change (%) (4)=(3)/(2)
Operating income	OFM	OMS	9230.364 (316.835)	7834.431 (291.826)	1395.932 *** (210.218)	17.818%
		Both-use		13,147.460 (562.494)	−3917.092 *** (348.464)	−29.794%
	OMS	OFM	5644.804 (140.283)	5242.463 (118.224)	402.341 *** (76.256)	7.675%
		Both-use		8107.128 (234.574)	−2462.323 *** (126.451)	−30.372%
	Both-use	OFM	12,815.696 (467.332)	7702.333 (248.820)	5113.363 *** (286.021)	66.387%
		OMS		8410.071 (249.934)	4405.625 *** (278.754)	52.385%

Note: *** denote $p < 0.01$. Robust standard errors are presented in parentheses.

Table 8. The result of winsorizing at the 1st and 99th percentiles.

Variable	Actual Selection	Counterfactual Selection	Actual Income (1)	Counterfactual Income (2)	ATT (%) (3) = (1)−(2)	Change (%) (4) = (3)/(2)
Operating income	OFM	Non-use	8951.523 (290.948)	7759.388 (325.778)	1192.135 *** (271.916)	13.318%
	OMS		5634.825 (140.105)	5510.340 (208.618)	124.485 (154.699)	2.209%
	Both-use		12,410.235 (423.580)	9735.241 (486.847)	2674.994 *** (409.748)	21.555%

Note: *** denote $p < 0.01$. Robust standard errors are presented in parentheses.

Table 9. The results of changing the independent variable.

Variable	Actual Selection	Counterfactual Selection	Actual per Capita Income (1)	Counterfactual per Capita Income (2)	ATT (3)=(1)−(2)	Change (%) (4)=(3)/(2)
Per capita Operating income	OFM	Non-use	2251.028 (64.035)	1870.692 (72.147)	380.336 *** (55.002)	20.331%
	OMS		1573.406 (36.337)	1389.730 (40.014)	183.676 *** (31.479)	13.217%
	Both-use		3276.248 (116.424)	2241.397 (82.162)	1034.851 *** (94.860)	46.170%

Note: *** denote $p < 0.01$. Robust standard errors are presented in parentheses.

Table 6 presents the ATU of the control group. The data in column (3) show that farm households that do not use farm machinery will significantly increase their operating income if they choose to use farm machinery. The data in column (4) show that the operating income of the households that do not use farm machinery will increase by 43.753%, 21.192%, and 69.908%, if they use self-owned farm machinery, outsourced farm machinery services, and jointly use the two types of farm machinery, respectively. Thus, H1 and H2 were validated. Finally, this paper visualizes the data of Table 6, which are shown in Figure A2.

Combining the results of Tables 5 and 6, we found that the joint use of the two types of farm machinery had the strongest effect on increasing income. Table 7 further illustrates the ATT of selection changes within the treatment group. The results in column (3) show that both farm households using self-owned farm machinery and those using outsourced farm machinery services have significantly higher operating income if they choose to jointly use both types of farm machinery. Further, we found that for both farm households using self-owned agricultural machinery and those using outsourced services, their incomes will decline if they exchange choices with each other. The above results suggest that self-owned farm machinery as well as outsourced machinery services are not substitutes but rather complements. Thus, H3 was validated. The combined use of both kinds of farm machinery brings a superimposed effect in increasing operating income, probably because of the differences in the power and application aspects of both kinds of farm machinery [5]. For those farm households who are willing to expand their agricultural operating income, the joint use of both types of farm machinery is optimal.

In the preceding sections, this study primarily focused on comparing the income gaps between factual and counterfactual situations under different adoption decisions, estimating ATT and ATU. Referring to Amankwah et al. [78], this paper further compared the operating income among four groups of farm households in actual conditions. Based on the data from column (1) of Table 5 and column (1) of Table 6, this study presented the kernel density distribution of the predicted operating income (log) for four groups of farm households under actual conditions (Figure 2). Figure 2 illustrates that the kernel density distribution curves of households using farm machinery are significantly shifted to the right compared to those not using any machinery. Furthermore, the kernel density distribution curves of farm households that jointly use two types of farm machinery are the most to the right.

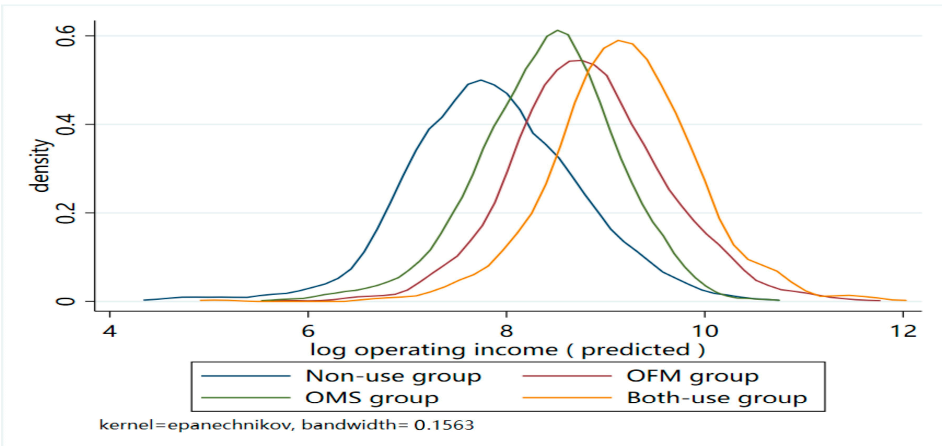

Figure 2. Kernel density distribution of farm households' actual operating income by adoption status.

5.3. Robustness Tests

To control the impact of extreme values on the results, following Pan et al. [55], this paper chose to conduct robustness tests in two ways: the first method was to winsorize operating income at the 1st and 99th percentiles; the second was to replace household operating income with per capita operating income. The outcomes of the two robustness tests are reported in Tables 8 and 9, which are generally consistent with the previous estimates. Differently, using outsourced machinery services significantly increased per capita operating income. However, the per capita operating income of farm households using outsourced machinery services was still smaller than that of the other two types of farm households using farm machinery, consistent with the previous study. Meanwhile, this difference may be due to the fact that households that do not use agricultural machinery have more children and unhealthy members who are not engaged in agriculture as part of the labor force, resulting in lower per capita operating income.

6. Dicussion

The findings of this study demonstrate that household head, family, village, and regional characteristics affect farm households' choice of farm machinery, which is consistent with the results of existing studies [28,31,36]. Meanwhile, this paper finds that the joint use of two types of farm machinery causes the greatest increase in farmers' operating income, suggesting that self-owned farm machinery and outsourced machinery services are complementary, which confirms the results of Qian et al. [5]. However, as research progresses, we observed that there are some differences in the characteristics of self-owned farm machinery and outsourced machinery services, which may be taken into account by farm households in the process of choosing farm machinery. Additionally, different crops may have varying demands for technological investment, which impacts the choice of farm machinery by farmers. However, since the CFPS dataset does not provide specific information on the types of crops farmed, this study will address this issue through a review of the relevant literature. The risk appetite of farm households may also affect their adoption decisions [36,82,83]. Meanwhile, the mechanisms through which farm machinery adoption affects farm households' operating income still need to be discussed. This paper will further analyze these issues in this section.

6.1. Factors Affecting the Adoption of Farm Machinery

As demanders of farm machinery, farm households decide on adopting farm machinery based on their resource conditions and the characteristics and availability of the two types of farm machinery. The resources of farm households consist mainly of three aspects: labor, land and capital. Human resources are measured mainly by the age, gender, and education level of the household head, as well as the input of the agricultural labor force. Land resources are mainly measured by the land scale and land transfer rate. Financial resources are measured mainly through the costs of seeds, etc., government grants, and borrowing. As noted previously, self-owned farm machinery complements the labor force, while outsourced machinery services replace the labor force. Farm households with a large-scale farming operation are more inclined to purchase self-owned farm machinery [31], and through the complementarity of the labor force and farm machinery, they achieve an increase in total factor productivity and exploit economies of scale. Smallholder farmers, who are relatively poor in terms of labor, land, and capital, can make up for the lack of labor by using relatively low-priced outsourced machinery services, as well as avoiding the high cost of purchasing self-owned farm machinery. However, farmers' willingness does not reflect their actual purchasing behavior [29], which also requires the effective supply of the market. The relatively higher price of agricultural machinery stimulates the efficient supply of the market, so here we focus on the market supply of agricultural machinery services. Village topography, distance to the nearest market town, and region reflect the potential transaction costs for farmers to access agricultural machinery services. Eastern, plain, and near-town areas have lower transaction costs for outsourced machinery services and a more efficient market supply, and are more likely to use outsourced machinery services.

In the previous section, this paper highlighted that the number of crop types managed reflects farmers' willingness and ability to engage in agricultural production, which positively influences their adoption of personal farm machinery. However, it is essential to analyze farmers' adoption behavior of machinery for specific crops. Specifically, Chinese farmers primarily cultivate crops such as rice, corn, wheat, potatoes, soybeans, and rapeseed [84,85]. With the advancement of agricultural mechanization, the labor intensity associated with these crops has continuously decreased [86]. However, the level of mechanization in production varies among different crops. Corn, rice, wheat, and soybeans have higher levels of mechanization [13,87], making it easier for farmers to access outsourced services from the market. Conversely, crops like potatoes and rapeseed have lower levels of mechanization [88,89], making it challenging for farmers to access outsourced services, leading them to rely more on manual labor or invest in self-owned machinery.

Farmers' personal preferences also affect their farm machinery adoption decisions [36]. Generally, farmers encounter risks related to institutions, information, bureaucracy, costs, and markets in production. This paper primarily examines farmers' preferences at two levels: their risk preference for adopting new technologies, and their preference for natural risks in agricultural production. The use of self-owned farm machinery requires farm households to have specialized skills and entails potential repair and maintenance costs. Adopting outsourced machinery services does not require specialized skills, and farm households are able to monitor the quality of the services. Therefore, risk-averse farm households are more likely to adopt outsourced machinery services [36]. However, for risk appetite farm households, if they acquire the skills to use farm machinery, they can use it with high frequency and have a greater potential for income growth. Natural risks constrain the level of operating income [90]. Chen et al. noted that that farm operation risks influence labor allocation between farm and off-farm sectors [91]. For risk-averse farm households, they reduce labor force inputs in agriculture and invest them in the non-farm sector for a more stable income. Outsourced machinery services can substitute for agricultural labor and address the needs of risk-averse farm households.

In summary, farm households make finite rational decisions about adopting farm machinery, considering their limited labor, land, and capital resources while also accounting for the transaction costs, crops cultivated and their personal preferences.

6.2. Impacts of the Adoption of Farm Machinery on Operating Income

The results of this paper show that the joint use of two types of agricultural machinery has the greatest impact on the growth of operating income. However, the reasons for this phenomenon have yet to be studied.

Agricultural production is a long-cycle, multi-step process that generally includes plowing, sowing, field management, and harvesting. Usually, plowing, sowing, and harvesting are labor-intensive stages, and it is easy to achieve standardized and mass production by replacing the labor force. Additionally, the effects of outsourced machinery services in these processes can also be directly supervised by farmers on the spot [92], which facilitates building trust. Thus, the proportion of farm households using outsourced machinery services is relatively large in these processes. In contrast, irrigation, fertilization, and pesticide application are technology-intensive processes where achieving standardized production is challenging due to differences in farmers' production philosophies. Moreover, in these stages, the effects of outsourced services require subsequent supervision. Therefore, farmers generally prefer not to outsource these intermediate processes but instead use self-owned machinery for production. Meanwhile, Liu et al. [93] highlight that in the pest and disease management phase, the lack of scale economies in outsourced services results in a shortage of specialized service provision.

Thus, the application of the two types of agricultural machinery differs: self-owned machinery is primarily used in technology-intensive stages, while outsourced machinery services are mainly utilized in labor-intensive stages. This study's findings reveal that farmers who jointly use both types of farm machinery achieve the highest income, followed by those that use only self-owned farm machinery, and those that use only outsourced machinery services the least. The joint use of two types of farm machinery has a superimposed effect on income generation. Pest and disease control, along with other field management tasks, are some of the most time-consuming aspects of agriculture. Increasing labor and machinery investment during this stage has the most significant impact on boosting income. Hence, farmers who utilize only self-owned machinery have higher incomes compared to those who rely solely on outsourced machinery services. For farm households that jointly use two types of farm machinery, they implement a differentiated resource allocation for different segments of agricultural production, rather than blindly pursuing the maximization of inputs such as labor, reflecting the idea of "differential optimums" [94,95].

In summary, the use of agricultural machinery has increased operating income, but there are differences in the yield-enhancing benefits of self-owned farm machinery and outsourced machinery services because they are used in different segments.

7. Conclusions, Policy Implications and Perspectives

7.1. Conclusions

On the basis of 2018 CFPS data, this paper employs the MERS model to investigate the elements affecting the adoption of farm machinery and its impact on the operating income of farm households. Three main findings were obtained.

First, the characteristics of the household head, family, village, and region influence households' adoption of farm machinery. Specifically, large-scale farm households with more labor, land, and financial resources are more inclined to utilize self-owned agricultural machinery to increase total factor productivity and to exploit scale effects. Small-scale farm households with fewer productive resources are more inclined to utilize outsourced machinery services to save on labor force costs. In between, medium-sized farm households are more inclined to jointly use self-owned farm machinery and outsourced farm machinery services.

Second, the adoption of self-owned farm machinery and the joint use of both types of farm machinery significantly increased operating income, while the effect of using only outsourced services was not significant. The farm household that jointly used two types of farm machinery had the highest farm household income.

Finally, this study includes the adoption of self-owned agricultural machinery and outsourced farm machinery services by farm households in the same framework, which corroborates the findings of Qian et al. [5], demonstrating that self-owned farm machinery complements labor, outsourced machinery services substitute labor, and there exists a complementary relationship between self-owned and outsourced farm machinery.

7.2. Policy Implications

First, the government should increase both the amount and range of subsidies for purchasing farm machinery, reduce financial pressure on farm households to buy farm machinery, satisfy their needs for farm machinery with different applications and power, and solve the problems of fewer choices and insufficient funds for farm households to buy farm machinery. Additionally, the government should offer skills training to farm households to enhance their ability to operate machinery and encourage the efficient use of their self-owned farm machinery.

Secondly, the development of outsourced machinery systems should be improved to offer farm households more comprehensive, cost-effective, and efficient services. First, support should be provided to operational organizations that offer cross-regional outsourced machinery services for agricultural production and ensure adequate protection for the transportation of agricultural machinery across regions. Second, the creation of regional agricultural machinery service systems should be promoted and the provision of services for intermediate production stages enhanced, such as seeding and field management. This will offer services with local characteristics to complement the cross-regional agricultural service system.

Finally, it is necessary to improve the relevant policies to safeguard the needs of farm households for land, labor, and capital. First, the rural land transfer system should be improved to facilitate the transfer of abandoned land to family farms and large-scale production units, enhancing production scale and land use efficiency. Second, county economies should be developed to enable the free movement of labor between agricultural and non-agricultural sectors, ensuring farm households can earn incomes from both sectors. Third, the rural financial service system should be enhanced to offer more long-term, low-cost loans to meet farmers' capital needs for agricultural production. Finally, attention should be given to expanding investment in agricultural infrastructure construction, promoting the construction of field roads and water conservancy facilities, and advancing land levelling and contiguity to ensure that mechanized production can be effectively implemented.

7.3. Limitations and Perspectives

This paper still has some shortcomings. First, this study uses cross-sectional data, which cannot reflect the dynamic changes of farm households' behavior in adopting farm machinery. Second, it is difficult to measure the cost and intensity of farm households' use of farm machinery in qualitative studies. Future research could use a more multifaceted approach to study the behavior of farm households in adopting farm machinery

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Appendix A

Table A1. Instrumental variable validity test.

Test	Statistics	Statistics Value	*p*-Value
Under-identification test	Kleibergen-Paap rk LM	360.572	0.000
Weak instrumental test	Kleibergen-Paap rk Wald F	571.336	

Table A2. Estimation of the main equation for operating income (second stage of MESR).

Variable	Non-Use		OFM		OMS		Both-Use	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Age	−0.000	0.009	−0.015	0.009	−0.016 **	0.008	0.003	0.011
Gender	0.323 *	0.183	0.294 *	0.176	0.261 *	0.155	0.014	0.198
Education level	−0.054	0.088	−0.056	0.076	0.059	0.056	0.076	0.063
Health	−0.052	0.063	−0.046	0.054	0.039	0.045	0.063	0.051
Internet	0.309	0.197	0.069	0.155	−0.270	0.167	−0.190	0.167
Land scale	−0.007	0.007	0.001	0.001	−0.007	0.010	0.001	0.004
Land renting-in	0.585 ***	0.290	−0.059	0.215	0.129	0.158	0.331 ***	0.167
Land renting-out	−0.141	0.241	−0.219	0.208	−0.238 *	0.137	−0.008	0.176
Agricultural labor force	0.112	0.117	0.289 ***	0.081	0.177	0.118	0.133	0.141
Off-farm employment	0.127	0.082	−0.122	0.087	−0.102	0.077	−0.102	0.117
Loan	−0.228	0.210	−0.063	0.176	−0.123	0.195	−0.037	0.141
Grant	−0.127	0.164	−0.022	0.174	0.087	0.160	0.077	0.190
Cost	0.273 **	0.107	0.605 ***	0.098	0.580 ***	0.165	0.500 ***	0.177
Social Network	0.046	0.028	0.056 *	0.033	0.032	0.020	0.061	0.039
Types	0.173 *	0.102	0.124 **	0.061	0.102	0.075	−0.017	0.110
Topography	−0.178	0.237	0.431 **	0.211	0.242	0.279	0.222	0.404
Distance	−0.025	0.016	−0.017	0.015	−0.043 **	0.021	−0.023	0.020
Region	−0.243 *	0.128	−0.311 **	0.117	−0.062	0.109	−0.050	0.150
Constant	6.420 **	1.234	2.268	1.611	4.033 ***	1.160	3.892 *	2.075

Table A2. *Cont.*

Variable	Non-Use		OFM		OMS		Both-Use	
	Coef.	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Ancillary								
σ^2	8.972	6.008	3.252 *	1.800	3.002	3.972	2.111	8.353
λ_1			−0.076	0.219	−0.211	0.435	0.612	0.505
λ_2	0.137	0.489			0.706	0.628	−0.247	0.768
λ_3	0.781 *	0.427	−0.482	0.590			−0.252	0.716
λ_4	−0.901 **	0.326	0.124	0.436	−0.382	0.257		
Observations	851		875		891		687	

Note: *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$.

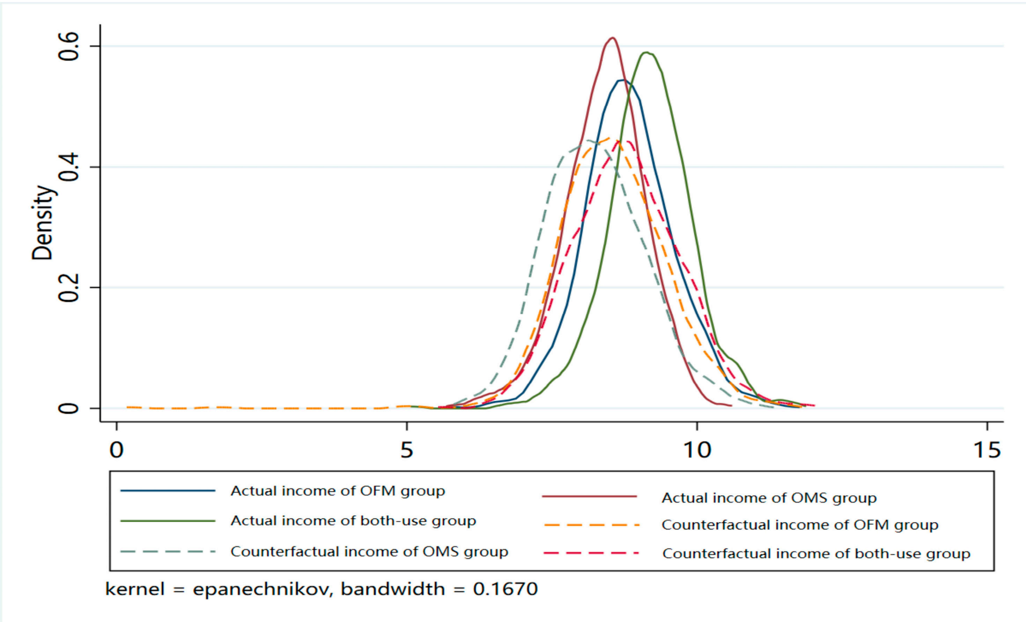

Figure A1. Kernel density in two situations of the treated group.

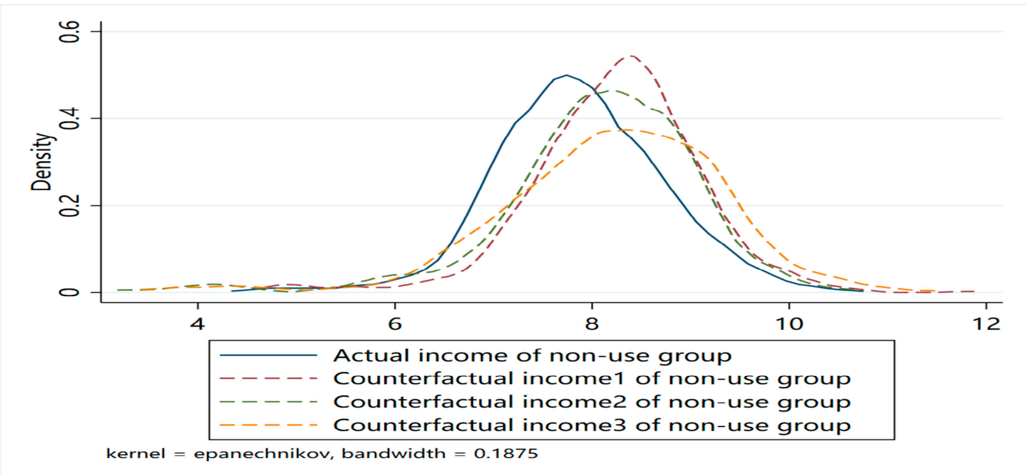

Figure A2. Kernel density in two situations of the untreated group.

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