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Adoption mode of agricultural machinery and food productivity: evidence from China

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Many researchers argue that the adoption of agricultural mechanization services (AMSs) is an important way for smallholder farmers in China to engage in modern agricultural production. However, the impact of the adoption mode of agricultural machinery on food productivity remains under-analyzed. We investigate the links between the adoption mode of agricultural machinery and food productivity using data on 795 grain farmers collected from the North China Plain. The results indicate that, compared with service outsourcing (SO), self-purchase (SP) improves the technical efficiency of farms; however, it reduces the input efficiency of agricultural machinery. The channel of the effect is that, although SO can reduce the redundancy of agricultural machinery's input, the opportunistic behavior of AMS suppliers and labor supervision problems lead to a decline in agricultural machinery's operation quality. The impact of the adoption mode of agricultural machinery on food productivity is asymmetrical among different types of farmers. Large-scale and professional farmers benefit more from SP, whereas small-scale and part-time farmers benefit more from SO. The AMS is not perfect, and the Chinese government should pay close attention to the loss of technical efficiency in agricultural production caused by the opportunistic behavior of AMS suppliers. Therefore, it is necessary to adjust the agricultural machinery subsidy policy and reduce the transaction cost of AMS.

KEYWORDS

agricultural mechanization services, adoption mode, food productivity, opportunistic behavior, transaction cost

1 Introduction

According to data from the Chinese Third National Agricultural Census, China has 207 million agricultural households with an average cultivated land area of 0.107 ha. This statistical data indicates that smallholder farmers comprise most agricultural households in China. Agricultural machinery has high investment costs, low frequency of use, and long return periods. Therefore, smallholder farmers lack the ability and incentives to invest in agricultural machinery. Thus, it is difficult for agriculture with smallholder farmers to realize mechanization (Feder et al., 1985; Ruttan, 2001). However, agricultural mechanization services (AMSs) have rapidly developed in China over the past century. China's agriculture has quickly achieved mechanization based on small-scale land operations (Yang et al., 2013; Zhang et al., 2017). AMSs break the traditional judgment that it is difficult to achieve agricultural mechanization with smallholder farmers. Farmers outsource agricultural machinery operations to AMS suppliers. By purchasing AMS, farmers solve the problem of labor shortages without investing in agricultural machinery (Ji et al., 2012; Yang et al., 2013). However, the AMSs are not unique to China. Although the government directly established the agricultural mechanization service enterprise centers (AMSECs), the market for AMS is still underdeveloped in Ghana (Houssou et al., 2013; Diao et al., 2014). AMS has developed slowly in Indonesia and Bangladesh (Paman et al., 2016; Mottaleb et al., 2017). The rapid development of the Chinese AMS market is attributed to the government's subsidy policy and strong extension services (Yang et al., 2013).

Mechanization has become an important driving force in China's food production and agricultural productivity growth (Wang et al., 2016; Sheng and Chancellor, 2019). Several studies have investigated the relationship between the AMS and food productivity. However, they provide both hypothetically plausible and empirically supported but contradictory theories. Some studies have found that AMSs lead to the principal–agent problem between farmers and AMS suppliers, which damages food productivity (Hayami and Otsuka, 1993; Coelli and Battese, 1996), whereas others have shown that AMSs improve food productivity by replacing labor inputs and standardized operations (Yang et al., 2016; Yi et al., 2019; Shi et al., 2021; Huan et al., 2022; Yang and Li, 2022). Under the influence of unfavorable conditions, such as small-scale farming, serious land fragmentation, aging, and feminization of the labor force, China's food productivity has become a public concern. However, few studies have identified the impact of adopting modes of agricultural machinery on food productivity. Farmers have adopted two modes of agricultural machinery: service outsourcing (SO), in which farmers outsource agricultural machinery operations to AMS suppliers, and self-purchase (SP), in which farmers themselves perform agricultural machinery operations. Does the adoption mode of agricultural machinery influence food productivity?

The transaction cost theory states that buying products from the market and producing products by the company are two different transaction mechanisms with different transaction costs (Coase, 1937; Williamson, 1979). Farmers outsource agricultural machinery operations to AMS suppliers. The outsourcing behavior poses an uncertain risk that increases outsourcing costs, specifically transaction costs (Feng et al., 2019). In agricultural production, supervising employee labor is difficult. Therefore, the food productivity of self-employed farms is significantly higher than that of hired farms (Coelli and Battese, 1996). This result indicates that the productivity of farms adopting AMS may be lower than that of farms purchasing agricultural machinery for self-operation. To fill this gap in the literature, this study provides a robust estimation of the effects of the adoption mode of agricultural machinery on food productivity as well as of the mediating role of the operation quality and input of agricultural machinery.

This study contributes to the existing literature in two ways. To the best of our knowledge, this study is the first to evaluate the impact of the adoption mode of agricultural machinery and food productivity. Studies have evaluated the impact of purchasing AMS on costs (Qiu and Luo, 2021), input factor structure (Yi et al., 2019), labor allocation (Liu et al., 2016), and efficiency (Zheng et al., 2021; Huan et al., 2022; Zhou and Ma, 2022). However, minimal direct research has been conducted on the adoption of agricultural machinery. This study addresses this gap and provides systematic evidence of whether and how the mode of adoption of agricultural machinery affects food productivity. Second, SO and SP are two distinct technology adoption modes. Existing studies focus on the positive impact of purchasing AMS on agricultural production compared to not using agricultural machinery (Ji et al., 2012; Yang et al., 2013; Deng et al., 2020; Shi et al., 2021; Xue et al., 2022), but they have rarely distinguished the differences between SO and SP. Against the backdrop of the decline in the AMS market, the difference between SO and SP must be seriously considered. This study addresses this gap by conducting a transaction cost analysis of SO and SP. Our findings show that SP improves technical efficiency but reduces the input efficiency of agricultural machinery compared to SO, which subverts the existing literature on the role of AMS. The findings of this study are very interesting in a typical "small farmers—large machinery."

The tests conducted in this study have 3-fold aims: First, we investigate the relationship between the adoption mode of agricultural machinery and food productivity; second, the mechanism through which the mode of adoption of agricultural machinery affects food productivity is tested using various methods; and third, we discuss the asymmetric characteristics of the different types of farmers. This helps to explain the responses of food productivity to the adoption mode of agricultural machinery and explore why the adoption mode of agricultural machinery affects food productivity.

2 Theoretical analysis

It is necessary to clarify the relationship among concepts of AMS, SO, and SP before discussing the impact of the adoption mode of agricultural machinery on food productivity. First, SO and SP are two completely opposite modes of agricultural machinery use. If SO is chosen as the method of using agricultural machinery, farmers need to outsource fieldwork to third-party AMS suppliers (Yang et al., 2013; Zhang et al., 2017). If SP is chosen as the method of using agricultural machinery, farmers need to purchase and drive agricultural machinery to complete the task of fieldwork. The market for agricultural machinery leasing is lacking, which means that the model of renting agricultural machinery is rarely seen (Zheng et al., 2021). The model of purchasing agricultural machinery and hiring workers to drive it to complete fieldwork under small-scale operation is basically non-existent (Deng et al., 2020). Therefore, SO and SP as two alternative modes are the focus of this study. Second, the China Agricultural Machinery Industry Yearbook defines the relationship between AMS and SP. SP, agricultural machinery sales service, agricultural machinery maintenance service, and agricultural machinery maintenance service are all included in the AMS market. According to the data of the China Agricultural Machinery Industry Yearbook, the total revenue of the AMS market in 2021 was 481.621 billion yuan, of which the total revenue of SP was RMB¥ 367.592 billion, accounting for 76.32% of the total revenue of the AMS market. Therefore, SP is the most important part of the AMS market. However, compared with 2015, the total revenue of the AMS market in 2021 decreased by RMB¥ 70.577 billion, which is considered to be related to the decrease of SP and the increase of SO (Wei and Lu, 2023).

A theoretical framework was developed to assess the relationship between agricultural machinery adoption modes and food productivity. The adoption modes of agricultural machinery can be divided into SO and SP. It is unclear whether the SP will lead to higher food productivity than the SO because there are few direct studies on the relationship between the adoption mode of agricultural machinery and food productivity, as previously discussed. The scope of labor division between the SP and SO is different. Farmers who choose SO are involved in the division of the labor economy by purchasing services from third-party suppliers, which belong to the market division of labor. Farmers who choose SP are involved in the division of the labor economy by purchasing agricultural machinery for self-service, which belongs to the internal division of labor on family farms. The space for labor division in agricultural production is extremely limited because of the difficulty of labor supervision (Coelli and Battese, 1996). Smith (1776) and Marshall (1961) believed that agricultural production is unsuitable for the division of labor and outsourcing. The scope of the labor division is an important factor affecting transaction costs (Williamson, 1979; Shi and Yang, 1995). This is similar to the relationship between enterprises' internal management costs and market transaction costs, as discussed by Coase (1937). Farmers who choose SO must bear the transaction cost of purchasing AMS, including the information search cost of AMS, the cost of bargaining with AMS suppliers, and the labor supervision cost of AMS suppliers. The Chinese government has issued several policies, such as organizing cross-regional harvesting, developing operational information management systems, and issuing service contract models, to reduce information and contract costs (Qiu and Luo, 2021). These measures reduce the SO's information searches and bargaining costs.

However, the challenge of labor supervision for AMS suppliers, which arises from the fundamental characteristics of agricultural production, remains difficult to address (Abd Latif and Kadhim, 2018; Wei and Lu, 2023). The basic characteristic of agricultural production is that the timing of crop growth is inconsistent with that of labor. This suggests that inputs and outputs in the agricultural production process do not align in a one-to-one correspondence. Therefore, farmers cannot measure the quality of AMS operations based on crop yield. Second, it is difficult to assess the work quality of onsite AMS suppliers. Farmers could not observe the depth of the cultivated land, density of sowing, or loss of harvesting. Third, farmers cannot assess the quality of their work by observing the physical and verbal performances of AMS suppliers. Therefore, information asymmetry in the operational quality of agricultural machinery between farmers and AMS suppliers is serious. Moreover, improving information asymmetry is difficult owing to the characteristics of agricultural production. In the case of information asymmetry, AMS suppliers with information advantages are motivated to engage in opportunistic behavior. These services aim to reduce fuel consumption, operation time, and machinery depreciation, which may involve practices, such as shallow tillage, uneven sowing, and excessive harvest losses. The opportunistic behavior of AMS suppliers, which cannot be supervised, leads to a loss of agricultural output. This loss reduces the food productivity. However, the SP can perfectly avoid the transaction costs and labor supervision problems of the SO. Therefore, the SP may increase technical efficiency compared with the SO.

While SP may enhance technical efficiency, it might simultaneously increase the redundancy of agricultural machinery inputs, thereby reducing overall input efficiency. Agricultural machinery is a specialized asset that must match sufficient land. Otherwise, it would be difficult to take full advantage of the scale benefits of agricultural machinery. Therefore, if the farmland scale of the farmers who choose SP is not sufficiently large, it will increase the redundancy of the agricultural machinery's input and make the agricultural machinery idle. Additionally, the increasing amount of agricultural machinery in China has intensified competition in the AMS market. Thus, it is increasingly difficult for farmers who choose SP to dilute the cost of agricultural machinery by providing AMSs to others. Therefore, the SP may reduce the input efficiency of agricultural machinery compared to the SO.

Many farmers have adopted AMS, which has accelerated the development of China's AMS market. China's practice seems to contradict Smith and Marshall's theoretical view of "Deepening division of labor in agricultural production has natural endogenous obstacles." Compared with the SP, the adoption mode of agricultural machinery (SO) improves the input efficiency of agricultural machinery and allows farmers to use it at the lowest cost. However, it declines technical efficiency. Therefore, farmers who adopt AMS pursue family income maximization at the expense of technical efficiency.

3 Methodology

3.1 Data

The data used for statistical analysis were obtained from a farm survey conducted in the North China Plain in 2020. The surveyed provinces included Henan, Hebei, and Shandong, which are the core components of the North China Plain. Household-level data on agricultural production and family characteristics were also collected. This survey focuses on farmers' adoption of agricultural machinery and its influence.

In terms of survey methodology, we conducted an eight-wave farm survey. We used stratified random sampling to select household farms. We selected Jing, Wuqiang, Gaocheng, Wenshang, Guan, Yucheng, Xingyang, and Sui counties as the sample areas, which are located in the core area of the North China Plain and are China's major food-producing counties. We conducted a farm survey in each county, leading to a total of eight farm surveys. The sampling process consists of three steps: First, 3–4 townships in each county were randomly selected based on their level of economic development; second, 2–3 villages from each township were randomly selected based on their level of economic development; and third, 15–20 household heads from each were randomly selected. The eight-wave survey included 840 observations. As 19 farm households contained missing values and 26 farm households did not plant grain, their data were removed, and a sample of 795 grain farmers was used in this study. Moreover, the same survey methodology was used to collect data on AMS suppliers. Because 12 AMS suppliers contained missing values and 10 AMS suppliers quit the AMS market for the first time, their data were removed, and a sample of 338 AMS suppliers was used in this study.

3.2 Variables

The dependent variable in this study is food productivity. The literature uses land output (or output value) to indicate food productivity, such as the average yield of crops, the natural logarithm of total yield, and the net output value (Muyanga and Jayne, 2019; Sheng et al., 2019; Qiu et al., 2020). However, higher levels of land output (or output value) may not be the most effective measure of food productivity (Yan et al., 2019). Drawing on the methods of existing research, this study uses the input and output of agricultural production factors to calculate the inefficiency of technology and uses technical efficiency and input efficiency for agricultural machinery to represent food productivity.

Technical efficiency is the decision-making unit's ability to maximize the output under the premise that the input does not change. Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are the commonly used methods for measuring technical efficiency, but neither incorporates relaxation improvement into the efficiency measurement process. As the bias of DEA and SFA poses problems in our estimates, the super-efficient slack variable slack-based model (SBM) proposed by Tone (2001, 2002) was used to measure farm technical efficiency. Introducing relaxation variables into the objective function and subdividing the effective decision-making units are the advantages of the SBM. The linear programming formula for farm technical efficiency is as follows:

$$\mu = \min\left[\frac{1}{m}\sum\nolimits_{i=1}^{m}\frac{\overline{X}}{X_{ik}}\right] \div \left[\frac{1}{q}\sum\nolimits_{s=1}^{q}\frac{\overline{Y}}{Y_{sk}}\right]. \tag{1}$$

The constraint conditions are follows:

$$\text{s.t.}\begin{cases} \overline{X} \geq \sum\nolimits_{j=1,j\neq k}^{n}\gamma_j X_{ij} \\ \overline{Y} \leq \sum\nolimits_{j=1,j\neq k}^{n}\gamma_j Y_{sj} \\ \overline{X} \geq X_k, \overline{Y} \leq Y_k \\ \gamma_j \geq 0, \sum\nolimits_{j=1,j\neq k}^{n}\gamma_j = 1, \end{cases} \tag{2}$$

where Equation (1) is the objective function, and Equation (2) is the constraint condition, μ denotes farm technical efficiency of the j-th farmer, X_{ik} represents the i-th input of the j-th farmer, Y_{sj} represents the s-th output of the j-th farmer, γ_j denotes the weight, $\overline{X}$ represents the amount of adjustment of the input indicator, and $\overline{Y}$ represents the amount of adjustment for the output indicator. The input factors for grain production include seeds, pesticides, fertilizers, irrigation, agricultural machinery, and labor (Yan et al., 2019; Yi et al., 2019). Therefore, we selected them as the input variables for wheat and corn crops per mu. The yield is inaccurate when measuring output owing to differences in grain quality (Yan et al., 2019). We selected the grain (wheat and corn) output value per mu as the output variable. There were differences in the values of grains of different qualities. For example, the value of the first-class wheat was higher than that of the second-class wheat. If only grain yield is used to measure output, it will not reflect differences in grain quality. The output value can be used to measure the differences in both yield and quality. Table 1 describes the input–output variables and summary statistics.

Factor input efficiency refers to the gap between the possible optimal input quantity and the actual input quantity when the total output and other factor inputs remain unchanged. We used the methods by Kaneko et al. (2004) and Hu et al. (2006) to measure factor input efficiency. The input efficiency of the agricultural machinery is determined according to Equation (3):

$$\text{MachinIE}_j = \frac{\left|\text{Minput}_j - \overline{X_j}\right|}{\text{Minput}_j}, \tag{3}$$

where $MachinIE_j$ denotes the agricultural machinery input efficiency for the j-th farmer, $Minput_j$ represents the actual input amount of agricultural machinery of the j-th farmer, and $\overline{X_j}$ is the slack amount in the agricultural machinery's input of the j-th farmer calculated from the super-efficient slack variable model. From Equation (3), it can be observed that $MachinIE$ satisfies $0 \leq MachinIE \leq 1$; the lesser slack, the closer the input efficiency of agricultural machinery is to 1, and the higher the input efficiency.

The primary focus of this study is to analyze the influence of agricultural machinery adoption modes on food productivity. The North China Plain is a two-cropping area per year, where wheat and corn are alternately planted, and there are six tasks of agricultural machinery. Wheat production tasks include machine farming, machine sowing, and machine harvesting. Corn is exempt from arable land in the North China Plain, and its tasks include machine sowing, machine harvesting, and straw return. This dummy variable is commonly used in the literature (i.e., outsourcing or non-outsourcing) (Yi et al., 2019; Xue et al., 2022). However, the continuous/count version (the number of tasks for SP) was more informative than the dummy (outsourcing or non-outsourcing). The utilization rate of agricultural machinery for the six tasks in the 795 households in the survey is 100%. Therefore, the sum of tasks for service outsourcing (SO) and self-purchase (SP) is six. The number of tasks for SP is used as a characterization variable for the farm's adoption mode of agricultural machinery. The greater the SP's task number, the lower the SO's task number.

The characteristic variables of an individual, family, and location affect their food productivity. First, age, gender, education, health, and job affect food productivity (Newman et al., 2015; Amare and Shiferaw, 2017; Deng et al., 2020); therefore, we controlled for householder characteristics [e.g., age, gender, education, self-identified health, working experience, agricultural training, Communist Party of China (CPC) identity, and village cadre identity]. Second, land size, off-farm employment,

TABLE 1 Input and output variables for computing technical efficiency.

Classification	Variable name	Mean	SD
Input variable	Seed cost per mu[a] (yuan)	114.43	27.81
	Fertilizer cost per mu (yuan)	319.18	60.96
	Pesticide cost per mu (yuan)	78.56	41.77
	Irrigation cost per mu[b] (yuan)	118.79	83.12
	Working days per mu[c]	10.35	8.63
	Machinery cost per mu[d] (yuan)	290.08	67.14
Output variable	Output value per mu (yuan)	2,001.64	332.80

[a] 1 mu = 1/15 ha.
[b] Irrigation cost includes water and electricity bills.
[c] 8 h per working day.
[d] The cost of SO is the price of AMS, the cost of SP includes mechanical depreciation, fuel consumption, labor, maintenance.

cooperative membership, and income affect food productivity (Rozelle et al., 1999; Alene and Manyong, 2007; Qiu et al., 2020); therefore, we controlled for the variables of household characteristics (e.g., land size, land fragmentation, labor structure, cooperative membership, and family income). Third, Newman et al. (2015) and Alves and Kato (2018) found that distance and regional conditions affect food productivity; thus, we controlled for distance and region dummy variables. Table 2 presents the model variables and summary statistics.

3.3 Empirical model

First, we assess the relationship between the mode of adoption of agricultural machinery and food productivity. The model is expressed as follows:

$$\mathrm{Apefficien_i} = \alpha_0 + \alpha_1 \mathrm{Mode_i} + \sum\nolimits_{j=1}^{n} \beta_j \mathrm{X_{ij}} + \epsilon_{\mathrm{i},} \tag{4}$$

where $Apefficien_i$ denotes food productivity, which is measured by the super-efficient slack variables SBM and **Equation (3)**. $Mode_i$ represents the adoption mode of agricultural machinery, which takes the value of the task number of an SP. X_{ij} are the control variables, including age, gender, education, and health. α_0 is a constant term. α_1 and β_j are the regression coefficients to be estimated. ϵ_i is the random error, which is assumed to be independent and normally distributed.

Omitting important variables and reverse causality may confound our parameter estimations, and hence, the statistical inference. To some extent, reverse causality of the adoption mode of agricultural machinery on food productivity exists. Farmers with higher agricultural productivity are more likely to own agricultural machinery and become SP-based specialists. In addition, although we controlled for variables, such as land and income, which might affect food productivity, we may have missed some unobservable variables, such as the household head's production preferences.

We use the instrumental variable (IV) method to solve the above endogenous issues. The average service acreage per horsepower of AMS suppliers at the town level was utilized to serve as the IV. Regarding the exogeneity and exclusion restrictions of the IV, first, the average service acreage per horsepower of AMS suppliers is a town-level variable, which means that the dependent variable cannot inversely affect the IV, and the IV is exogenous to the dependent variable considerably. Second, the service radius of the Chinese AMS market continues to shrink, and the proportion of long-distance inter-provincial services continues to decline (Qiu and Luo, 2021). Of the 338 AMS providers surveyed, 266 offered AMSs within their town limits. Therefore, the supply of agricultural machinery to towns is insufficient. In this case, farmers will adopt the SO model more frequently. Conversely, farmers adopted the SP model. The average service acreage per horsepower of AMS suppliers at the town level can affect food productivity only by affecting farm households' adoption mode of agricultural machinery, i.e., the IV exclusion restriction. The two-stage least squares method is suitable for situations where the endogenous variable is a continuous variable.

The endogenous variable is an ordinal index, and the two-stage least squares method cannot be used to estimate the model parameters. Instead, we used a conditional mixed process (CMP). The CMP allows for continuous, binary, and ordered endogenous variables.

To test why farms with different agricultural machinery adoption modes have different food productivity levels, we assessed the mediating effect of the operation quality and input of agricultural machinery. The four models were as follows:

$$\mathrm{Quality_i} = \delta_0 + \delta_1 \mathrm{Mode_i} + \sum\nolimits_{j=1}^{n} \theta_j \mathrm{X_{ij}} + \epsilon_{\mathrm{i}} \tag{5}$$

$$\mathrm{Apefficien_i} = \gamma_0 + \gamma_1 \mathrm{Mode_i} + \gamma_2 \mathrm{Quality_i} + \sum\nolimits_{j=1}^{n} \sigma_j \mathrm{X_{ij}} + \epsilon_i \tag{6}$$

$$\mathrm{Minput_i} = \mu_0 + \mu_1 \mathrm{Mode_i} + \sum\nolimits_{j=1}^{n} \rho_j \mathrm{X_{ij}} + \epsilon_{\mathrm{i}} \tag{7}$$

$$\mathrm{Apefficien_i} = \varphi_0 + \varphi_1 \mathrm{Mode_i} + \varphi_2 \mathrm{Minput_i} + \sum\nolimits_{j=1}^{n} \tau_j \mathrm{X_{ij}} + \epsilon_i, \tag{8}$$

where $Quality_i$ represents the farmer's evaluation of the operational quality of agricultural machinery. Indicators such as the depth of cultivated land, the density of sowing, and the cleaning loss during harvesting are used as technical indicators to measure the quality of agricultural machinery operations (Banerjee and Punekar, 2020). However, in the questionnaire survey, technical indicators are difficult to observe. Previous studies have used subjective evaluation indicators to measure objectively existing transaction costs (Abd Latif and Kadhim, 2018; Mugwagwa et al., 2020). Therefore, the subjective evaluation of the quality of agricultural machinery operation by farmers is used as a measure of the quality of agricultural machinery operation, which takes a value of 1–5 (1 = very bad, 2 = bad, 3 = central, 4 = good, and 5 = very good). $Minput_i$ denotes the cost of machinery input per mu (yuan), which we deal with logarithmically as follows: The cost of the SO is the price of AMS per mu, and the cost of SP includes mechanical depreciation, fuel, labor, and maintenance costs per mu. δ_0 and μ_0 are constant terms. δ_1, θ_j, μ_1, and ρ_j are the estimated parameters.

The causal step method was first used to test the mediating effect (Baron and Kenny, 1986). However, when the mediating effect is small, the applicability of the causal-step method is weakened. The Sobel and bootstrap methods were used to replace the causal-step method (Mackinnon et al., 2007; Hayes, 2009). In contrast to the causal step method, the Sobel and bootstrap methods directly test the mediating effect. Due to the limitations of a single test method, this study employed the causal step, Sobel, and bootstrap methods simultaneously to test the mediating effect. The number of repeated samples in the bootstrap method was set to 1,000.

4 Results

4.1 Baseline regression

4.1.1 The impact of the adoption mode of agricultural machinery on food productivity

Table 3 reports the estimation results for **Equation (4)**. The values of technical and input efficiencies are limited dependent variables. Therefore, we use both the ordinary least squares (OLS) method and Tobit models to estimate **Equation (4)**. The results

TABLE 2 Variable definitions and summary statistics.

Variable name	Definition	Mean	SD
Technical efficiency	Calculated by the super-efficient slack variable SBM	0.745	0.198
Input efficiency	Calculated by Equation (3)	0.977	0.080
Machinery mode	The SP's task-number	1.193	1.845
Age	Age of the household head (years)	56.435	10.481
Gender	1 if the household head is male and 0 otherwise	0.860	0.347
Education	Education of the household head, 1 = uneducated, 2 = elementary school, 3 = junior high school, 4 = high school or secondary school, 5 = junior college, 6 = college and above	2.688	0.818
Health	Self-identified health of the household head, 1 = very good, 2 = good, 3 = central, 4 = bad, 5 = very bad	4.152	0.908
Non-farm employment	1 if the household head has non-farm employment experience within the last 3 years, and 0 otherwise	0.352	0.478
Agricultural training	1 if the household head has received agricultural training, and 0 otherwise	0.343	0.475
CPC identity	1 if the household head is a CPC member, and 0 otherwise	0.253	0.435
Village cadre identity	1 if the household head is a village cadre, and 0 otherwise	0.141	0.348
Land size	Size of land operated by the farm household (mu)	53.064	101.638
Land fragmentation	The proportion of land parcels <1 mu	0.116	0.357
Labor force	The number of able-bodied persons over the age of 16 in the farm household[a]	3.024	1.213
Agricultural labor	Proportion of the labor force mainly engaged in farming in the farm household	0.330	0.288
Aging labor	Proportion of aging labor in farm household[b]	0.577	0.416
Non-farm income	Proportion of non-farm income to total farm household income	0.436	0.365
Cooperative membership	1 if the farm household has cooperative membership, and 0 otherwise	0.133	0.340
Distance to county town	Distance between county town and home of the farm household (km)	16.080	7.901
Province dummy	Province dummy variable	—	—

[a]Campus students in farm household are not counted.
[b]The aging labor includes people over 60 years of age who are engaged in labor activities.

in columns (1) and (3) are estimated using the OLS method. The results in columns (2) and (4) are estimated using the Tobit model. The results indicate that the SP increases technical efficiency but reduces the input efficiency of agricultural machinery compared with the SO.

The estimated results in columns (1) and (2) indicate that the mode of agricultural machinery adoption positively affects technical efficiency at the 5% significance level. As the SP's task number increases and the SO's task number decreases, the technical efficiency of the farmers increases. The estimated results in columns (3) and (4) indicate that the agricultural machinery adoption mode negatively affects the input efficiency of agricultural machinery at the 1% significance level. As the SP's task number increases and the SO's task number decreases, the input efficiency of farmers decreases. The estimated results support our previous theoretical framework that the SP increases technical efficiency but reduces the input efficiency of agricultural machinery compared with the SO. The adoption of an AMS is a double-edged sword, which improves the input efficiency of agricultural machinery at the expense of technical efficiency.

4.1.2 Results of control variables

Among the other control variables, we found that male household heads have higher food productivity than female household heads. The higher the educational level, the higher the technical efficiency, which is consistent with common sense. Health status is positively correlated with the input efficiency of agricultural machinery, which means that farmers with a higher health status are more efficient in using agricultural machinery. Household heads with non-agricultural employment experience have higher technical efficiency. A possible explanation is that non-agricultural employment experience helps to broaden the household heads' vision and improve the ability of farmers to accept new technologies.

The higher the proportion of agricultural labor, the higher the technical efficiency. CPC identity reduces the input efficiency of agricultural machinery. The higher the proportion of non-agricultural income, the lower the importance of agricultural income. Therefore, the proportion of non-agricultural income reduces both technical and input efficiencies. Farmers who joined cooperatives had higher technical and input efficiencies. The other control variables had insignificant impacts on food productivity.

4.2 Robustness check

4.2.1 Analysis of endogenous problems

We used the CMP method to correct for potential endogenous problems. Table 4 presents the results of CMP estimation. The

TABLE 3 Impacts of agricultural machinery's adoption mode on food productivity.

Variable name	Technical efficiency		Input efficiency	
	(1)	(2)	(3)	(4)
Machinery mode	0.019** (0.009)	0.017** (0.008)	−0.008*** (0.003)	−0.071*** (0.026)
Age	0.001 (0.001)	0.000 (0.000)	−0.000 (0.000)	−0.002 (0.003)
Gender	0.059*** (0.017)	0.056*** (0.014)	0.006 (0.006)	0.031 (0.055)
Education	0.016** (0.007)	0.017** (0.007)	−0.003 (0.004)	−0.027 (0.027)
Health	−0.000 (0.008)	0.004 (0.006)	0.004** (0.002)	0.043* (0.025)
Non-farm employment	0.046*** (0.014)	0.037*** (0.011)	−0.006 (0.007)	−0.032 (0.042)
Agricultural training	0.001 (0.016)	0.000 (0.013)	−0.001 (0.007)	−0.045 (0.046)
CPC identity	0.015 (0.016)	0.005 (0.011)	−0.017** (0.007)	−0.109*** (0.041)
Village cadre identity	0.009 (0.019)	0.016 (0.018)	0.023 (0.015)	0.038 (0.051)
Land size	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.001* (0.001)
Land fragmentation	0.009 (0.016)	0.006 (0.013)	−0.011 (0.006)	−0.063 (0.048)
Labor force	0.005 (0.007)	0.007 (0.005)	0.003 (0.003)	0.027 (0.022)
Agricultural labor	0.076*** (0.029)	0.060*** (0.024)	−0.013 (0.011)	−0.118 (0.097)
Aging labor	0.009 (0.016)	0.010 (0.015)	−0.005 (0.006)	−0.021 (0.066)
Non-farm income	−0.050** (0.024)	−0.039** (0.019)	−0.029*** (0.009)	−0.209*** (0.079)
Cooperative membership	0.067*** (0.024)	0.054*** (0.014)	0.012*** (0.004)	0.160** (0.080)
Distance to county town	−0.001* (0.001)	−0.001* (0.001)	−0.000 (0.000)	0.001 (0.004)
Province dummies	Yes	Yes	Yes	Yes
Constant	0.582*** (0.081)	0.600*** (0.057)	1.010*** (0.023)	1.552*** (0.243)
R-squared (Pseudo R^2)	0.269	−0.812	0.265	0.406
Observations	795	795	795	795

Robust standard errors are presented in parentheses; *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

estimation results in column (1) show that IV has a negative impact on the adoption mode of agricultural machinery at the 1% significance level, indicating that IV satisfied the correlation condition. The endogenous test parameters (atanhrho_12) of technical efficiency in the first stage of CMP do not pass the significance test. Regarding the impact of the adoption mode of agricultural machinery on technical efficiency, the endogenous threat is proven to be untenable, which shows that results (1) and (2) of Table 2 are reliable.

The estimation result in column (3) shows that atanhrho_12 in the input efficiency of agricultural machinery passes the significance test at the 1% level, indicating that endogenous problems exist in the impact of agricultural machinery's adoption mode on the input efficiency of agricultural machinery. The second-stage estimation results of CMP in column (4) show that the adoption mode of agricultural machinery negatively affects its input efficiency at the 10% significance level. Therefore, after correcting for the endogenous problem in the baseline regression, the same conclusions are reached. By comparing with SO, SP improves the technical efficiency of farms; however, it reduces the input efficiency of agricultural machinery, which means that our conclusions are still valid. Notably, the control variable results are consistent with those in Table 3; therefore, we have not shown the control variable results in Table 4.

4.2.2 Replace core variables

The adoption of agricultural machinery is reflected in two ways. The first aspect is the AMS expenditure of farmers: the more the AMS expenditures, the more agricultural machinery operation tasks farmers outsource, indicating that the SO model is being adopted more frequently. The proportion of AMS expenditures was used as an alternative to the adoption mode of agricultural machinery. The second aspect is the amount of investment in agricultural machinery. If farmers buy agricultural machinery, they are more likely to serve themselves, indicating that the SP mode will be adopted. The average investment in agricultural machinery per mu was used as an alternative variable for the adoption mode of agricultural machinery.

The robustness test results are shown in Table 5. The proportion of AMS expenditure significantly reduced farmers' technical efficiency but improved the input efficiency of agricultural machinery. Conversely, agricultural machinery investment per mu significantly improves farmers' technical efficiency but reduces the input efficiency of agricultural machinery. The results in Table 5 show that the SP increases technical efficiency but reduces the input efficiency of agricultural machinery compared with the SO, which supports the baseline regression results.

TABLE 4 Results of CMP estimation.

Variable name	Technical efficiency		Input efficiency	
	(1) First-stage	(2) Second-stage	(3) First-stage	(4) Second-stage
Machinery mode$^{I\hat{V}*}$		0.018 (0.013)		−0.008* (0.004)
IV for machinery mode	−2.489*** (0.396)		−2.498*** (0.396)	
Atanhrho_12	0.035 (0.233)		0.018** (0.008)	
Control variables	Yes	Yes	Yes	Yes
Province dummies	Yes	Yes	Yes	Yes
Wald chi2	409.76		347.62	
Observations	795		795	

Robust standard errors are presented in parentheses; *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

TABLE 5 Robustness test results.

Variable name	(1)	(2)	(3)	(4)
	Technical efficiency	Input efficiency	Technical efficiency	Input efficiency
AMS expenditure ratio	−0.077* (0.045)	0.371** (0.148)		
Investment of agricultural machinery			0.119*** (0.027)	−0.138*** (0.040)
Control variables	Yes	Yes	Yes	Yes
Province dummies	Yes	Yes	Yes	Yes
Constant	0.673*** (0.073)	1.260*** (0.275)	0.517*** (0.055)	1.143*** (0.258)
R-squared (Pseudo R^2)	−0.804	0.418	−0.846	0.422
Observations	795	795	795	795

Robust standard errors are presented in parentheses; *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

4.3 Heterogeneity analysis

4.3.1 Heterogeneity of land scale

Is the effect of the adoption mode of agricultural machinery on food productivity symmetrical among different types of farmers? That is, who benefits the most from the AMS market? The World Bank distinguishes between large and small farms based on a land-scale standard of 30 mu. Therefore, 30 mu is regarded as the boundary of the farmers' grouping to construct a dummy variable for the land scale. Even when the model settings are completely consistent, we cannot directly compare two coefficients using group regression because we cannot determine that the random perturbation terms of the regression equations between different groups are uncorrelated. Cross terms are introduced into heterogeneity analysis to address the issue of direct grouping coefficients that cannot be compared (Greene, 2012).

Table 6 reports the estimated results of introducing interaction term coefficients. Rows (1)–(3) in Table 6 report the results of the interaction between the dummy variable of land scale and the adoption mode. In the regression equation of technical efficiency, the interaction coefficient of machinery mode and dummy variable of land scale is positive, which is significant at the 1% level. This result indicates that, with the expansion of the farmland scale, the positive impact of SP on technical efficiency is amplified. In the regression equation of input efficiency, the interaction coefficient of machinery mode and dummy variable of land scale is negative, which is significant at the 1% level. This result indicates that, with the expansion of the farmland scale, the negative impact of SP on input efficiency is reduced. The coefficients of the interaction term indicate that, compared with SO, SP has a greater positive incentive effect on the technical efficiency of large farmers but a greater negative impact on the agricultural machinery input efficiency of small farmers.

4.3.2 Heterogeneity of age

Farmers' ages were divided into three equal parts: 16–32 years old are young farmers, 33–57 years old are farmers, and 58–82 years old are elderly farmers. Using young farmers as the control group, the dummy variables of middle-aged and elderly farmers were constructed. Rows (4)–(7) in Table 6 report the results of the interaction between the dummy variable of age and the adoption mode. The coefficients of the interaction term do not pass the significance test, which indicates that the heterogeneity characteristics of age are not significant.

4.3.3 Heterogeneity of non-agricultural income

The farmers were divided into three groups according to the proportion of their non-agricultural income. The proportion of non-agricultural income is <10% for professional farmers, 10–50% for "part-time I" farmers, and more than 50% for "part-time

TABLE 6 The results of group estimation.

Variable name	Interaction term	Technical efficiency	Input efficiency
Land size	Dummy variable of land scale	0.109*** (0.021)	−0.252*** (0.069)
	Machinery mode	0.018** (0.007)	−0.075*** (0.028)
	Machinery mode × Dummy variable of land scale	0.004*** (0.001)	−0.013*** (0.004)
Age	Dummy variable of age	0.004 (0.007)	−0.029 (0.023)
	Machinery mode	0.017** (0.008)	−0.072*** (0.027)
	Machinery mode × Middle-aged	−0.007 (0.030)	0.025 (0.018)
	Machinery mode × Elderly	−0.010 (0.013)	0.000 (0.037)
Nonfarm income	Dummy variable of Nonfarm income	−0.032*** (0.011)	−0.006*** (0.002)
	Machinery mode	0.017** (0.008)	−0.071*** (0.025)
	Machinery mode × Part-time I	−0.002*** (0.000)	0.016 (0.003)
	Machinery mode × Part-time II	−0.005 (0.021)	0.020*** (0.004)

Robust standard errors are presented in parentheses; *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

II" farmers. Using professional farmers as the control group, the dummy variables of "part-time I" and "part-time II" farmers were constructed.

Rows (8)–(11) in Table 6 report the results of the interaction between the dummy variable of non-farm income and the adoption mode. In the regression equation of technical efficiency, the interaction coefficient of machinery mode and part-time I is negative, which is significant at the 1% level. In the regression equation of input efficiency, the interaction coefficient of machinery mode and part-time II is positive, which is significant at the 1% level. The coefficients of the interaction term indicate that, compared with SO, SP has a greater positive incentive effect on the technical efficiency of professional farmers; however, it has a greater negative impact on the agricultural machinery input efficiency of "Part-time II" farmers. Large and professional can achieve greater efficiency improvements from the SP. Conversely, small and part-time farmers can achieve greater efficiency improvements from SO.

4.4 Life mechanism analysis identifiers

4.4.1 Quality of agricultural machinery operation

Table 7 reports the results of the mediating effect test. Owing to the heterogeneity of regression methods, it is meaningless to calculate the size of the mediating effect. Therefore, we do not report the size and proportion of mediating effect. The results of the causal step method show that SP improves the quality of agricultural machinery operation. After both the adoption mode of agricultural machinery and the quality of agricultural machinery operation are incorporated into the model simultaneously, neither the adoption mode of agricultural machinery nor the quality of agricultural machinery operation is significant. According to the causal step method, the Sobel test and the bootstrap method should be used for further testing. The mediating effect test results of the Sobel test and the bootstrap method are consistent. The mediating effect coefficients all passed the significance test at the 1% level, and the 95% confidence interval under the bootstrap method does not contain 0, indicating that the mediating effect of the quality of agricultural machinery operation is established. The transmission path of "machinery mode → quality of agricultural machinery operation → technical efficiency" is proven. SP improves technical efficiency by increasing the quality of agricultural machinery operation.

4.4.2 Agricultural machinery's input

The second factor was the mediating effect of agricultural machinery inputs per mu. The results of the causal step method show that SP improves the agricultural machinery input per mu. After the adoption mode of agricultural machinery and the agricultural machinery input per mu were incorporated into the model simultaneously, the adoption mode of agricultural machinery was not significant, indicating that a complete mediating effect was established. The mediating effect test results for the Sobel and bootstrap tests were consistent. The mediating effect coefficients passed the significance test at the 1% level, and the 95% confidence interval under the bootstrap test did not contain zero, which supports the results of the causal step method. The transmission path of "machinery mode → agricultural machinery's input per mu → input efficiency" is proven. SP reduces input efficiency by increasing agricultural machinery's input per mu.

5 Discussion

5.1 Adoption model of agricultural machinery and AMS market

In recent decades, with the development of the AMS market, China has rapidly realized agricultural mechanization based on smallholder farmers. China has blazed a special path toward achieving agricultural mechanization (Yang et al., 2013; Zhang et al., 2017). However, the AMS market capacity began to decline.

TABLE 7 Estimation result of the mediating effect.

Variable name	(1) Oprobit Quality of agricultural machinery operation	(2) Tobit Technical efficiency	(3) OLS Agricultural machinery's input per mu	(4) Tobit Input efficiency
Causal steps method				
Machinery mode	0.665*** (0.078)	0.012 (0.008)	0.077*** (0.099)	−0.037 (0.026)
Quality of agricultural machinery operation		0.004 (0.008)		
Agricultural machinery's input per mu				−1.468*** (0.200)
Control variables	Yes	Yes	Yes	Yes
Province dummies	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.283	−1.003	0.776	0.629
Number of observations	795	795	795	795
Variable name	Machinery mode → quality of agricultural machinery operation → technical efficiency		Machinery mode → agricultural machinery's input per mu → input efficiency	
Sobel test	0.011*** (0.003)		−0.006*** (0.002)	
Bootstrap test	0.010*** (0.003)		−0.006*** (0.002)	
95% conf. interval (*P*)	[0.175, 0.420]		[−0.581, −0.239]	
Control variables	Yes		Yes	
Province dummies	Yes		Yes	
Number of observations	795		795	

Robust standard errors are presented in parentheses. *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

First, according to the China Agricultural Machinery Industry Yearbook, AMS revenue continued to decline after reaching its peak in 2015, and the profit margin of agricultural mechanization in 2019 was nearly 5% lower than that in 2015. Second, the number of AMS practitioners decreased from 55.715 million in 2015 to 53.412 million in 2019. The number of AMS professionals annually decreased from 5.2508 million in 2014 to 4.243 million in 2019. Third, the cross-regional harvested areas of wheat, rice, and corn peaked in 2013 but showed a downward trend after 2013. The cross-regional harvested area of wheat decreased from 14.426 million ha in 2013 to 6.035 million ha in 2019, indicating a decrease of 58.17%. The cross-regional harvested area of rice decreased from 7.696 million ha in 2013 to 4.473 million ha in 2019, indicating a decrease of 41.88%. The cross-regional harvested area of corn decreased from 3.251 million ha in 2013 to 2.57 million ha in 2019, indicating a decrease of 20.95%. Many studies have discussed the impact of the rapid development of the AMS market on farmer behavior, food production, and agricultural efficiency (Sheng and Chancellor, 2019; Yi et al., 2019; Zheng et al., 2021; Qiu and Luo, 2021). They focused on discussing the positive effects of AMS. Existing theories cannot explain the transition from prosperity to decline in the AMS market (Wei and Lu, 2023). However, the conclusions of this study provide a new perspective to explain this phenomenon. Compared to SP, SO improves the input efficiency of agricultural machinery but reduces technical efficiency. With the development of China's land transfer market, moderate-scale operations have been regarded as an important goal of the Chinese government to promote agricultural production. An increasing number of farmers are shifting from the SO mode to the SP mode, which has led to a recession in the AMS market.

5.2 Adoption mode of agricultural machinery and food productivity

Farmers are involved in the division of the labor economy through the SO model, and economies of scale of agricultural machinery are obtained by farmers without bearing the sunk costs of agricultural machinery (Yang et al., 2013). Developing an AMS is conducive to reducing farmers' sunk costs incurred from self-owned machinery assets and labor costs (Wang et al., 2016). Previous studies have shown that AMS solves the capital and labor constraints faced by farmers, thereby improving food efficiency (Zheng et al., 2021; Huan et al., 2022; Zhou and Ma, 2022). Although agricultural machinery services can enable small farmers to achieve the same technological progress as large farmers (Sheng and Chancellor, 2019), the results of this study show that agricultural machinery services cannot perfectly replace their own agricultural machinery. By comparing with SP, SO reduces the technical efficiency of agricultural production. The reason behind this is that SO has increased the transaction costs of outsourcing AMS. The opportunistic behavior of AMS suppliers reduces the quality of agricultural machinery, which poses a threat to technical efficiency. Unfortunately, existing literature has paid little attention to the issue of moral hazard for AMS suppliers.

Government should not be overly obsessed with the positive effects of AMS on agricultural production. They should be aware

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that farmers adopt AMS at the expense of technical efficiency in exchange for saving production costs, which is a manifestation of efficiency loss for a country's agricultural production. Notably, the Chinese government is currently cultivating family farms. It can be predicted that the AMS will decline in China with an increase in the number of large-scale operating farms. Therefore, the Chinese government's policies must be adjusted in a timely manner. Instead of blindly pursuing the development of the AMS market, the loss of technical efficiency in agricultural production caused by AMS should be corrected. The most effective way is to suppress the opportunistic behavior of AMS suppliers and reduce the information asymmetry of AMSs. Based on the results, this study puts forward two suggestions. First, the government should maintain a flexible subsidy policy for the purchase of agricultural machinery. According to the saturation state of agricultural machinery in the regional market, the scope and proportion of agricultural machinery subsidies need to be adjusted at any time. For example, in areas where the number of agricultural machinery is saturated, the government needs to reduce subsidies and encourage farmers to exchange old agricultural machinery for new ones. In areas where the number of agricultural machinery is insufficient, the government needs to increase subsidies. Second, the skill training of agricultural machinery hands is used to improve the proficiency of agricultural machinery hands. The government should regularly carry out business training for AMS suppliers, improve the quality of agricultural machinery operations, and reduce the transaction costs of service outsourcing.

5.3 Impact of agricultural machinery's adoption mode on food productivity in different situations

A few studies have compared the relationship between AMS and the food productivity of farmers of different sizes. However, the underlying mechanisms remain unclear. Some studies have found that small farms can obtain more benefits from AMS (Yi et al., 2019; Zhou and Ma, 2022), whereas others have shown that AMS has a greater positive impact on medium-sized farms (Qiu and Luo, 2021). The results of this study provide a new perspective for understanding AMS preferences of farms of different sizes. Compared to large farms, small farms have obtained greater efficiency improvements from SO. However, compared with small farms, large farms have obtained greater efficiency improvements from SP. The impact of adopting agricultural machinery on food productivity is asymmetrical among farmers of different sizes. Therefore, the Chinese government should not encourage AMS to be used by all farms but should encourage small farms to purchase AMS and large farms to purchase agricultural machinery for self-operation. Non-farm employed farmers can obtain more benefits from AMS (Ji et al., 2012; Yang et al., 2016), which is supported by the conclusions of this study. However, the results of this study indicate that professional farmers can obtain greater benefits from SP. Therefore, the behaviors of professional farmers purchasing agricultural machinery and that of non-farm employed farmers purchasing AMS should be supported.

5.4 Limitations and further research

Our study has some limitations. We examined the differences in food productivity between the SO and SP. However, apart from SO and SP, farmers also lease agricultural machinery in the North China Plain, although the leasing model is restricted to relatives, friends, and neighbors, and it accounts for very little market share. Owing to data limitations, we could not test the impact of leasing agricultural machinery on food productivity. Moreover, we concede that our measure of the quality of agricultural machinery operations may fail to fully capture the opportunistic behaviors of AMS suppliers. Therefore, information from interviews inevitably suffers from bias. In conclusion, we call for more detailed studies, given the differences between leasing agricultural machinery and AMS. There are two ways to mitigate these limitations in future studies: First, the technical indicators of agricultural machinery operation quality can be used to evaluate the transaction cost of AMS outsourcing. The technical indicators include the depth of cultivated land, planting density, and the loss of cleaning in harvest. The use of objective indicators helps to improve the accuracy of estimation. Second, on the basis of collecting data on agricultural machinery leasing, we call for more literature to discuss the impact of farmers' behavior of leasing agricultural machinery on food productivity.

The results indicate that, compared with service outsourcing (SO), self-purchase (SP) improves the technical efficiency of farms; however, it reduces the input efficiency of agricultural machinery. The channel of the effect is that, although SO can reduce the redundancy of agricultural machinery's input, the opportunistic behavior of AMS suppliers and labor supervision problems lead to a decline in agricultural machinery's operation quality. The impact of the adoption mode of agricultural machinery on food productivity is asymmetrical among different types of farmers. Large-scale and professional farmers benefit more from SP, whereas small-scale and part-time farmers benefit more from SO. The AMS is not perfect, and the Chinese government should pay close attention to the loss of technical efficiency in agricultural production caused by the opportunistic behavior of AMS suppliers.

6 Conclusion

In this study, we theoretically analyze the relationship between the adoption mode of agricultural machinery and food productivity. We then use survey data collected from 795 farm households in Henan, Hebei, and Shandong provinces in the North China Plain to empirically examine the impact of the adoption mode of agricultural machinery on food productivity. Based on these studies, the study draws meaningful conclusions. First, the results of baseline regression show that SP increases technical efficiency but reduces the input efficiency of agricultural machinery compared with the SO. However, baseline regression faces the challenge of endogenous problems. The CMP method is used to correct potential endogenous errors. After correcting for potential endogenous bias, this conclusion remained correct. Replacement variables are used to reproduce baseline regression results. This conclusion is consistent with the different variables. Second, this study employed the causal step, Sobel, and bootstrap methods simultaneously to test the mediating effect. The inspection results show that the operational quality and input of agricultural machinery mediate the relationship between the adoption mode of agricultural machinery and food productivity. The transmission path of "machinery mode → quality of agricultural machinery operation → technical efficiency" and "machinery mode → agricultural machinery's input per mu → input efficiency" has been proven to be stable and reliable. Third, the results of heterogeneity analysis show that the impact of the adoption mode of agricultural machinery on food productivity was moderated by farmland scale and non-agricultural income. Compared with SO, SP has a greater positive incentive effect on the technical efficiency of large farmers but a greater negative impact on the agricultural machinery input efficiency of small farmers. Compared with SO, SP has a greater positive incentive effect on the technical efficiency of professional farmers; however, it has a greater negative impact on the agricultural machinery input efficiency of "Part-time II" farmers. Large-scale and professional farmers benefit more from SP, whereas small-scale and part-time farmers benefit more from SO. We suggest that the government should adjust the subsidy policy for agricultural machinery in time to guide the balance of supply and demand of regional agricultural machinery. Meanwhile, the government needs to introduce policies aimed at reducing AMS transaction costs to improve food productivity. We call for the use of objective technical indicators to measure the transaction cost of AMS and discuss the differences between leasing agricultural machinery and AMS.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: the datasets generated and analyzed during the current study are available from the corresponding author on reasonable request. Requests to access these datasets should be directed to SW, wsh123@jlu.edu.cn.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

SW: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Resources, Software, Validation, Writing – original draft. YL: Formal analysis, Project administration, Supervision, Visualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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