Effects of Agricultural Mechanization on Land Productivity: Evidence from China

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Abstract
This study investigates the determinants of adoption of different mechanized farming strategies (i.e. no-mechanized farming, semi-mechanized farming, and full-mechanized farming) and their impacts on land productivity. An innovative multinomial endogenous switching regression model estimates farm household data derived from the China Labor-force Dynamics Survey. The empirical results show that farmers' decision to adopt semi-mechanized farming is positively affected by household size, access to credit, farm size, irrigation rate, subsidies, and machinery service; their decision to adopt full-mechanized farming is primarily determined by the age of household heads, farm size, land use certificate, subsidies, and machinery service. Adopting semi- and full-mechanized farming exerts positive impacts on land productivity, and the larger impact is associated with the adoption of full-mechanized farming. The disaggregated analyses indicate that female-headed households adopting semi-mechanized farming obtain higher land productivity relative to their male-headed counterparts; the farm size–land productivity relationship is positive for semi-mechanized farming adopters but negative for full-mechanized farming adopters; both semi- and full-mechanized farming adopters living in central China obtain the highest land productivity relative to their counterparts residing in the western and eastern China. The findings of this study have significant implications for sustainable production and food security.
Keywords: Agricultural mechanization; Land productivity; MESR; China
JEL codes: O13, Q12, Q15

1. Introduction

Improving land productivity is fundamental to facilitating sustainable agricultural production, ensuring food and nutrition security, alleviating poverty, and enhancing sustainable rural development (Adamopoulos and Restuccia, 2020; Asfaw et al., 2017; Bado et al., 2021; Helfand and Taylor, 2021; Zheng et al., 2021b). However, in recent decades, smallholder farmers in developing countries face acute issues, such as labor shortages because of rural-to-urban migration and rising labor costs (Liu et al., 2020; Paudel et al., 2019; Wang et al., 2016a; Zhou et al., 2018). These issues significantly challenge sustainable agricultural production and the growth of farm productivity, especially for labor-intensive crops such as rice and wheat. Paudel et al. (2019) revealed that farmers in the mid-hills of Nepal required more time for land preparation because of labor shortages, causing delayed seedling transplantation and lower rice productivity.

Adoption of mechanical technologies can help alleviate the labor bottlenecks, enhance agricultural production, and lower the unit cost of crop production (e.g., Amoozad-Khalili et al., 2020; Benin, 2015; Daum and Birner, 2020; Ma et al., 2018b; Paudel et al., 2019; Takeshima and Liu, 2020; Zhang et al., 2016; Zheng et al., 2021c). This is because mechanized agriculture improves the farm operation's timeliness, quality, and efficiency and reduces drudgery. Although agricultural mechanization brings significant benefits to agricultural production, its adoption rate remains low in developing countries (Adekunle et al., 2016; Benin, 2015; Qiao, 2017; Zhou et al., 2018). Qiao (2017) found that farm machines harvested 0.23% of the cotton in the major cotton-producing regions (excluding Xinjiang province) of China in 2014. Thus, understanding and identifying the constraints and incentives that influence smallholder farmers' decisions to mechanize agriculture and evaluate agricultural mechanisation's economic impacts would provide significant evidence to policymakers for designing better policy instruments.

Several studies have examined the nature and determinants of agricultural mechanization in rural areas of developing countries. Researchers have used three methods to measure agricultural mechanization, including binary machine use status (Aryal et al., 2019; Ji et al., 2012; Paudel et al., 2019; Takeshima et al., 2020; Zhang et al., 2019; Zhou et al., 2020), use of total machine horsepower or expenses on farm machine use (Wang et al., 2016b; Zhang et al., 2017), and machine use intensity or rate (i.e. the proportion of land cultivated land with farm machine adoption) (Baudron et al., 2019; Li et al., 2017; Ma et al., 2018b; Zheng et al., 2021c; Zhou et al., 2018). For example, Adekunle et al. (2016) showed that social structure, culture and religion, unemployment concerns, gender factors, and perceived consequences are the critical factors that affect the machine use rate in cassava cultivation in African countries. Wang et al. (2018) revealed that agricultural machination, proxied by farm household machine expenses in China, is mainly affected by farm size and land fragmentation. Using survey data from rural Bangladesh, Aryal et al. (2019) found that farmers' decision to adopt small-scale machines such as power tillers, threshers, and irrigation pumps are mainly affected by their off-farm work participation, market access, and economic position.

Studies examining the impacts of agricultural mechanization have focused on two strands. The first strand of literature has analyzed the impact of agricultural mechanization on technology adoption and crop yields (Benin, 2015; Ma et al., 2018b; Paudel et al., 2019; Takeshima et al., 2013; Zhang et al., 2019; Zhou et al., 2020). In their study for China, Zhang et al. (2019) revealed that farm machinery use significantly reduces the pesticide expenditure in maize production because it improves the efficiency of pesticide spraying. In an investigation of Nepal, Paudel et al. (2019) found that the adoption of scale-appropriate mechanization increases rice productivity by 1,110 kg/ha. The second strand of literature has revealed that agricultural mechanization promotes off-farm work participation of rural households (Ji et al., 2012; Ma et al., 2018b; Pingali, 2007; Zheng et al., 2021a) and empowers rural women in farm management (Adekunle et al., 2016; Fischer et al., 2018). Agricultural mechanization relieves the drudgery and frees households' farm management time that can be reallocated to off-farm activities. Additionally, men are more likely to migrate from rural areas to urban areas for better off-farm work opportunities, and women are usually left at home for farm management, leading to the so-called feminization of agriculture (Ma et al., 2018b). Agricultural mechanization enables and empowers rural women by being an alternative to labor in agricultural production and helps them maintain or increase crop productivity.

The studies mentioned above have provided insights into the determinants and impacts of agricultural mechanization. However, the findings cannot be generalized as they provide only a partial understanding of the relationship between agricultural mechanization and farm performance because of differences in natural resource endowments, economic development conditions, crop diversification, institutional arrangements, and geographic heterogeneities. For example, other studies have considered farmers' binary machinery use decision and machinery use intensity (Aryal et al., 2019; Ma et al., 2018b; Paudel et al., 2019; Takeshima et al., 2020; Zheng et al., 2021c; Zhou et al., 2020). However, none of them has considered farmers' mechanization adoption decision in a multiple-choice context.

In this study, we extend previous studies and make two significant contributions to the literature. First, we provide insights into the factors affecting farmers' decision to adopt three mutually exclusive mechanization strategies (i.e. no-mechanized farming, semi-mechanized farming, and full-mechanized farming) and assessing the impacts of agricultural mechanization adoption on land productivity. Land productivity is a preferred outcome indicator because it affects food security. Improving land productivity is also a pathway to achieve the "zero hunger" sustainable development goal promoted by the United Nations General Assembly in 2015. The open-access China Labor-force Dynamics Survey data (i.e. 6,447 rural households), collected by the Centre for Social Science Survey at Sun Yat-sen University (Guangzhou, China) in 2016, are used.

Second, we employ an innovative multinomial endogenous switching regression (MESR) model to control the selection bias issue that usually arises when agricultural mechanization is not randomly assigned and when the technology adoption involves more than two choices. The MESR model addresses the selection bias originating from both observed factors (e.g. age, off-farm work participation, gender, education, and location characteristics) and unobserved factors (e.g. farmers' innate ability, motivations to mechanize agriculture, and managerial skills) (Issahaku and Abdulai, 2020; Kassie et al., 2015; Khonje et al., 2018; Tesfaye et al., 2021). For robustness check, we also present the results estimated from a multivalued treatment effects model. Also, we explore the heterogeneous effects of agricultural mechanization on land productivity by gender, farm size, and geographic locations. This issue has been overlooked in the literature, despite the evidence that has demonstrated that gender (de Brauw et al., 2013; Kansanga et al., 2019), farm size (Adu-Baffour et al., 2019; Takeshima et al., 2020; Wang et al., 2018), and geographic locations (Ma et al., 2018b; Van Loon et al., 2020) determine rural farmers' mechanization adoption behaviors and agricultural productivity.

The rest of this paper is demonstrated as follows. Section 2 presents the analytical framework and the econometric approach. Section 3 introduces the data and descriptive statistics. The empirical results are presented and discussed in Section 4. The final section concludes with policy implications.

2. Analytical framework and econometric approach

2.1 Analytical framework

Farmers select themselves into adopting different mechanization strategies in farm production, depending on household and farm-level characteristics and other socio-economic determinants (Amoozad-Khalili et al., 2020; Ji et al., 2012; Ma et al., 2018b; Takeshima, 2017; Tesfaye et al., 2021). This phenomenon leads to a sample selection bias issue related to the mechanization adoption variable, which should be addressed to estimate the unbiased effects of agricultural mechanization adoption on land productivity. When selection involves only two options, namely, a farmer can choose either to adopt a technology or not to adopt it, other studies have employed both parametric approaches such as the endogenous switching regression model and non-parametric approaches such as propensity score matching to address the selection bias issue and estimate the effects of policy programs or technology adoption interventions (Adu-Baffour et al., 2019; Khonje et al., 2018; Liu et al., 2019; Paudel et al., 2019).

When the selection is of more than two options, the multivalued treatment effects (MVTE) model has been applied in the literature (Linden et al., 2016; Ma et al., 2018a). For example, using the MVTE model, Ma et al. (2018a) analyzed the impact of three types of dairy farming systems (i.e. low-, medium-, and high-input systems) on milk production and financial performance in New Zealand. They found that higher input systems perform significantly better physically than lower input systems do, but not financially. The major limitations of the MVTE approach are that it does not consider selection bias from unobserved factors, and it cannot estimate the determinants of land productivity because of the non-parametric nature of the model.

In this study, we model the impacts of the adoption of three agricultural mechanization strategies on land productivity within a MESR framework. Compared with the MVTE model, the MESR is a relatively new selectivity correction methodology that has three advantages: (a) it has the ability to address the selection bias originating from both observable and unobservable factors; (b) it enables the identification of factors affecting farmers' decision to adopt mechanization strategies and factors influencing land productivity; and (c) it captures the interactions between the choices of three mechanization strategies through selectivity correction terms (Di Falco and Veronesi, 2013; Khonje et al., 2018; Tesfaye et al., 2021; Vigani and Kathage, 2019).

2.2 Multinomial endogenous switching regression model

The estimation of the MESR model is conducted simultaneously in two stages. In the first stage, farmers' decision to choose to adopt different types of mechanization strategies are modeled using a multinomial logit (MNL) model. In the second stage, the land productivity equations, respectively, for no-mechanized adopters, semi-mechanized farming adopters, and full-mechanized farming adopters are estimated using ordinary least squares (OLS) regression models, in which the selectivity correction terms generated from the first stage of MNL model estimation are included. Afterwards, the effects of agricultural mechanization on land productivity are calculated by estimating the average treatment effects on the treated (ATT).

2.2.1 First stage estimation: modeling the determinants of agricultural mechanization adoption

We assume that risk-neutral farmers choose one of the three mutually exclusive mechanization strategies (i.e. no-mechanized farming, semi-mechanized farming, and full-mechanized farming) to maximize their utility in agricultural production. In this analytical setting, we assume for any individual farm household i that the expected utility obtained from choosing mechanization strategy j is A_{ij} and that it is derived from choosing any of the alternative options k is A_{ik}. In this case, a rational farm household i chooses to adopt mechanization strategy j only if $A_{ij}^* = A_{ij} - A_{ik} > 0$ $(j \neq k)$, where A_{ij}^* refers to the utility difference between adopting mechanization strategies j and k. A_{ij}^* is unobserved because it is subjective. Alternatively, A_{ij}^* can be expressed by a latent variable model as follows:

$$A_{ij}^* = Z_i \beta_j + \mu_{ij}, \qquad j = 1, 2, 3 \tag{1}$$

where Z_i represents a set of household and farm-level characteristics, j refers to a categorical indicator that describes a farmer's decision to choose the mechanization strategy j, β_j is a set of parameters, and μ_i is an error term. Although the expected utilities obtained from adopting two alternative mechanization strategies cannot be observed directly, a household i's decision to adopt the j-th mechanization strategy can be expressed by

$$A_i = \begin{cases} 1, & if \ A_{i1}^* > max_{j\neq 1}\left(A_{ij}^*\right) \\ 2, & if \ A_{i2}^* > max_{j\neq 2}\left(A_{ij}^*\right) \\ 3, & if \ A_{i3}^* > max_{j\neq 3}\left(A_{ij}^*\right) \end{cases} \tag{2}$$

where A_i is an index that denotes farmer i's choice of mechanization strategy. In particular, $A_i = 1$ if the farmer chooses no-mechanized farming, $A_i = 2$ if the farmer chooses semi-mechanized farming, and $A_i = 3$ if the farmer chooses full-mechanized farming. We referred to Bourguignon et al. (2007) to determine that the probability that farm household i with characteristics Z_i would choose the j-th mechanization strategy and can be estimated by an MNL model as follows:

$$P_{ij} = Pr\left(\tau_{ij} < 0|Z_i\right) = \frac{\exp(Z_i\beta_j)}{\sum_{j=1}^{3}\exp(Z_i\beta_j)}, \qquad j = 1, 2, 3 \tag{3}$$

where $\tau_{ij} = \max_{k\neq j}(A_{ik}^* - A_{ij}^*)$. P_{ij} is the probability of choosing to adopt no-mechanized farming ($j = 1$), semi-mechanized farming ($j = 2$), and full-mechanized farming ($j = 3$). A maximum likelihood method can be used to estimate the parameters of the MNL model in Equation (3).

2.2.2 Second stage estimation: modeling the determinants of land productivity

The second stage of the MESR model estimates the land productivity equations, respectively, for no-mechanized farming adopters, semi-mechanized farming adopters, and full-mechanized farming adopters, using OLS regression models. We referred to Di Falco and Veronesi (2013) and Vigani and Kathage (2019), and the outcome equation for each possible regime j is given as

$$\begin{cases} Regime\ 1\ (\text{no} - \text{mechanized farming adopters})\text{:} Y_{i1} = X_i\theta_1 + \varepsilon_{i1} \quad if \ A_i = 1 \\ Regime\ 2\ (\text{semi} - \text{mechanized farming adopters})\text{:} Y_{i2} = X_i\theta_2 + \varepsilon_{i2} \ \ if \ A_i = 2 \\ Regime\ 3\ (\text{full} - \text{mechanized farming adopters})\text{:} Y_{i3} = X_i\theta_3 + \varepsilon_{i3} \ \ if \ A_i = 3 \end{cases} \tag{4}$$

where Y_{ij} ($j = 1, 2, 3$) is the outcome variable (i.e. land productivity) of the i-th farm household in regime j, X_i represents a vector of explanatory variables (e.g. age, education, and household size) assumed to affect land productivity, θ_j ($j = 1,2,3$) refers to the corresponding parameters to be estimated, and ε_{ij} are the error terms with conditional zero means.

The selection bias from the observable factors can be taken into account by the control variables X_i in Equation (4). However, if there is selection bias from unobserved factors (e.g. farmers' motivations to mechanize agriculture and their farm managerial skills), the effects of agricultural mechanization on land productivity would be inconsistently estimated. In the MESR model framework, the selection bias from unobservable factors is addressed by the inclusion of the selectivity correction terms. In particular, the selectivity correction terms, calculated after estimating Equation (3), are automatically included in Equation (4) as additional regressors. Therefore, Equation (4) can be rewritten as follows:

$$\begin{cases} Regime\ 1\ (\text{no} - \text{mechanized farming adopters})\text{:} Y_{i1} = X_i\vartheta_1 + \lambda_1\sigma_1 + \nu_{i1} \ \ if \ A_i = 1 \\ Regime\ 2\ (\text{semi} - \text{mechanized farming adopters})\text{:} Y_{i2} = X_i\vartheta_2 + \lambda_2\sigma_2 + \nu_{i2} \ \ if \ A_i = 2 \\ Regime\ 3\ (\text{full} - \text{mechanized farming adopters})\text{:} Y_{i3} = X_i\vartheta_3 + \lambda_3\sigma_3 + \nu_{i3} \ \ if \ A_i = 3 \end{cases} \tag{5}$$

where Y_i and X_i ($j = 1, 2,\ 3$) are the aforementioned variables; ϑ_j and σ_j ($j = 1, 2,\ 3$) represent the corresponding parameters to be estimated; ν_{ij} ($j = 1,2,3$) refers to the error terms with an expected value of 0; λ_1, λ_2, and λ_3 refer to a vector of selectivity correction terms obtained from the first stage estimation of the MSER model; they are included in Equation (5) to correct for unobserved selection bias issues.[1] In the multinomial choice setting, there are $J-1$ selectivity correction terms to be included in each alternative mechanization strategy adoption scenario. Notably, if the coefficient of any of the selectivity correction terms is statistically significant, this would suggest the presence of unobservable selection bias (Kassie et al., 2015; Khonje et al., 2018; Tesfaye et al., 2021). Following Vigani and Kathage (2019), we estimate bootstrapped standard errors using Equation (5) to account for the heteroscedasticities from the generated regressors (λ_j).

2.3 MESR model identification

Notably, the variables X_i in Equation (5) and Z_i in Equation (1) are usually allowed to have the same explanatory variables. However, for MESR model identification purpose, at least one variable in Z_i should not be shown in X_i. Therefore, the MNL equation is estimated by employing the same variables included in the land productivity equation and at least one variable serving as an identifying instrument. A valid instrument should only influence farmers' decision to adopt different mechanization strategies but not directly affect land productivity. In this study, we employ a variable measuring the presence of a library in a village as an instrumental variable in Equation (1). The presence of a library in a village is hypothesized to affect farmers' choice of mechanization strategies. It is rational because farmers exposed to information through library access tend to be more aware of the benefits associated with agricultural mechanization; thus, they are more likely to adopt modern technologies such as farm machines. However, the employed instrumental variable is not expected to affect land productivity.

To ensure the employed instrumental variable is valid, we use two strategies to test it. First, we refer to Di Falco and Veronesi (2013) and conduct a simple falsification test. The results suggest that the library variable affects farmers' mechanization adoption significantly but not the outcome variables of interest. Second, a Pearson correlation analysis is used, and the results show that the library variable is significantly correlated with the mechanization adoption variable (coefficient=0.230, p-value=0.000), but it is not significantly associated with the land productivity variable (coefficient=0.012, p-value=0.328). The findings confirm that the library variable is appropriate to serve as a valid instrument.

2.4 Estimating the average treatment effects on the treated (ATT)

The estimations of the first and second stages of the MESR model provide a better understanding of the determinants of agricultural mechanization adoption and the determinants of land productivity. However, to analyze the treatment effects of the adoption of different mechanization strategies on land productivity, further calculations are required. We refer to Khonje et al. (2018) and Kumar et al. (2019) and estimate the average ATT by comparing expected outcomes for mechanization adopters and non-adopters in actual and counterfactual scenarios. In particular, the expected land productivity for semi- and full-mechanized farming adopters in an observed context is computed as

$$E\left(Y_{ij} \middle| A=j, X, \lambda_{ij}\right) = \vartheta_j X_i + \lambda_j \sigma_j, \qquad j = 2,3 \tag{6a}$$

The expected land productivity for semi- and full-mechanized farming adopters in a counterfactual context is given as

$$E\left(Y_{i1} \middle| A=j, X, \lambda_{ij}\right) = \vartheta_1 X_i + \lambda_j \sigma_1, \qquad j = 2,3 \tag{6b}$$

ATT can then be calculated as the difference between Equations (6a) and (6b):

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[1] The selectivity correction terms were calculated as $\lambda_j = \sum_{k\neq j}^{j} \rho_j \left[\frac{\widehat{P_{ik}} ln(\widehat{P_{ik}})}{1-\widehat{P_{ik}}} + ln(\widehat{P_{ij}})\right]$, where ρ_j refers to the correlation coefficient of the error terms ν_{ij} and μ_{ij}.

$$ATT = E\left[Y_{ij}\middle|A = j\right] - E\left[Y_{i1}\middle|A = j\right] = X_{ij}\left(\vartheta_j - \vartheta_1\right) + \lambda_j\left(\sigma_j - \sigma_1\right), \qquad j = 2, 3 \qquad (7)$$

3. Data and descriptive statistics

3.1 Data

The data used in this paper are derived from the 2016 China Labor-force Dynamics Survey (CLDS), which is conducted by the Centre for Social Science Survey at Sun Yat-sen University (Guangzhou, China). Using a multistage sampling method, the CLDS survey collects data from 29 provinces of mainland China (excluding Tibet and Hainan) and covers its western, central, and eastern regions. The sampling procedure ensures the collected information are nationally representative. The survey collects detailed information on personal and household-level characteristics, daily life activities of households, housing conditions, the financial performance of households, rural labor migration, and agricultural production and marketing.

The 2016 CLDS survey data comprises 14,200 samples: 8,248 rural households and 5,952 urban households. Because this study investigates the association between agricultural mechanization adoption and land productivity, the samples for urban households are excluded from the analysis. After data cleaning, 6,447 samples of rural households are used in the empirical models.

In this study, the treatment variable refers to three agricultural mechanization strategies adopted by smallholder farmers: no-mechanized farming (i.e. a farm machine is not used at any agricultural production stage), semi-mechanized farming (i.e. a farm machine is used at some agricultural production stages), and full-mechanized farming (i.e. a farm machine is used at every agricultural production stage). The outcome variable employed in this study refers to land productivity, which is defined as the total value of crop output per unit of land (i.e. yuan/mu). We consider the value of crop output rather than crop yields mainly because of the significant diversity of crops on the farms. We select the control variables by referring to other studies (e.g., Benin, 2015; Ma et al., 2018b; Mano et al., 2020; Mottaleb et al., 2017; Paudel et al., 2019; Takeshima, 2018; Takeshima et al., 2018; Tesfaye et al., 2021; Zhang et al., 2019; Zheng et al., 2021c; Zhou et al., 2020) and in consideration of data availability. In this study, we include variables representing age, gender and education of household heads, off-farm work participation status, household size, access to credit, farm size, land use certificate, irrigation rate, subsidies, machinery service, and location dummies as control variables.

3.2 Descriptive statistics

The definitions and summary statistics of the variables used in the econometric analysis are presented in Table 1. On average, land productivity is 822 yuan/mu.[2] The majority of households (61.5%) use no machines on their farms, reflecting the dominant role of traditional farming practices (no-mechanized farming) in China's agricultural production. Approximately 24.5% and 14.0% of the surveyed households have adopted the semi-mechanized and full-mechanized farming practices, respectively. The mean age of farming household heads is 54 years, and 60.1% are male. The education variable is specified by a category variable, and on average, the household heads' education is between primary school and middle school. Approximately 48.5% of household heads participated in off-farm work in 2015. The mean household size is approximately five persons, and on average, 33.2% of households have access to credit. The average farm size operated by farm households is 6.5 mu in 2015. Approximately 51% of households have received a land use certificate, and 26.6% of them have received the agricultural subsidy. Table 1 also shows that 27.4% of sampled households' village committees provide machinery service in the ploughing stage in 2015.

[2] Yuan is Chinese currency: 1 USD=7.00 yuan in June 2020; 1 mu=1/15 hectare.

Table 1 Variables definition and descriptive statistics

Variables	Definitions	Mean (S.D.)
Land productivity	Total value of crop output per unit of land (1,000 yuan/mu) [a]	0.822 (1.844)
No-mechanized farming	1 if household adopts no-mechanized farming, 0 otherwise	0.615 (0.487)
Semi-mechanized farming	1 if household adopts semi-mechanized farming, 0 otherwise	0.245 (0.430)
Full-mechanized farming	1 if household adopts full-mechanized farming, 0 otherwise	0.140 (0.348)
Age	Age of household head (years) [b]	53.738 (14.308)
Gender	1 if household head is male, 0 otherwise	0.601 (0.490)
Education	Educational level of household head [c]	2.477 (1.386)
Off-farm work	1 if household head works off the farm, 0 otherwise	0.485 (0.500)
Household size	Number of people residing in one household	4.704 (2.211)
Access to credit	1 if household has access to credit, 0 otherwise	0.332 (0.471)
Farm size	Total farm size cultivated by household (mu) [d]	6.497 (7.961)
Land use certificate	1 if household receives a formal land use right certificate, 0 otherwise	0.511 (0.500)
Irrigation rate	Ratio of irrigated land to total cultivated land (%)	0.468 (0.437)
Subsidy	1 if household receives cash subsidy for agricultural production, 0 otherwise	0.266 (0.798)
Machinery service	1 if the village committee provides the ploughing machinery service, 0 otherwise	0.274 (0.446)
West	1 if household resides in western China, 0 otherwise	0.368 (0.482)
Central	1 if household resides in central China, 0 otherwise	0.293 (0.455)
East	1 if household resides in eastern China, 0 otherwise	0.368 (0.482)
Library	1 if the village owns a library, 0 otherwise	0.766 (0.423)

Note: [a] 1 USD = 7.04 yuan in December 2019;
[b] Household head refers to the family member who dominates the decision-making in a household;
[c] 1= illiterate; 2=primary school; 3=middle school; 4=high school; 5= vocational high school; 6=technical school; 7= technical secondary school; 8=College; 9=bachelor; 10=postgraduate;
[d] 1 mu =1/15 hectare.

Figure 1 demonstrates the relationship between the adoption of different agricultural mechanization strategies and land productivity by gender and shows that land productivity differs between male- and female-headed households. For example, among no-mechanized and full-mechanized farming adopters, male-headed households obtain higher land productivity than their female-headed counterparts do. By contrast, female-headed households adopting semi-mechanized farming obtain higher land productivity than their male-headed counterparts do by adopting the same mechanization strategy. Figure 2 illustrates the relationship between the adoption of different agricultural mechanization strategies and land productivity by farm size. The figure shows that among semi-mechanized farming adopters, those cultivating medium farm size (3–6 mu) have the highest land productivity (i.e. 1,319 yuan/mu), and among full-mechanized farming adopters, those cultivating small farm size (≤3 mu) obtain the highest land productivity (i.e. 1,602 yuan/mu).

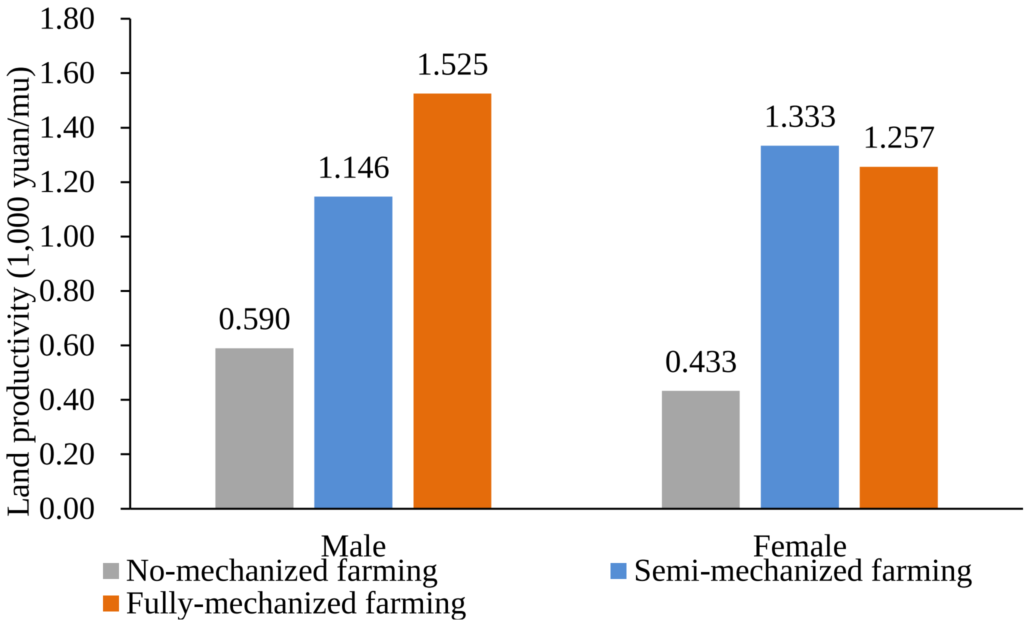

Figure 1 Relationship between agricultural mechanization and land productivity by gender

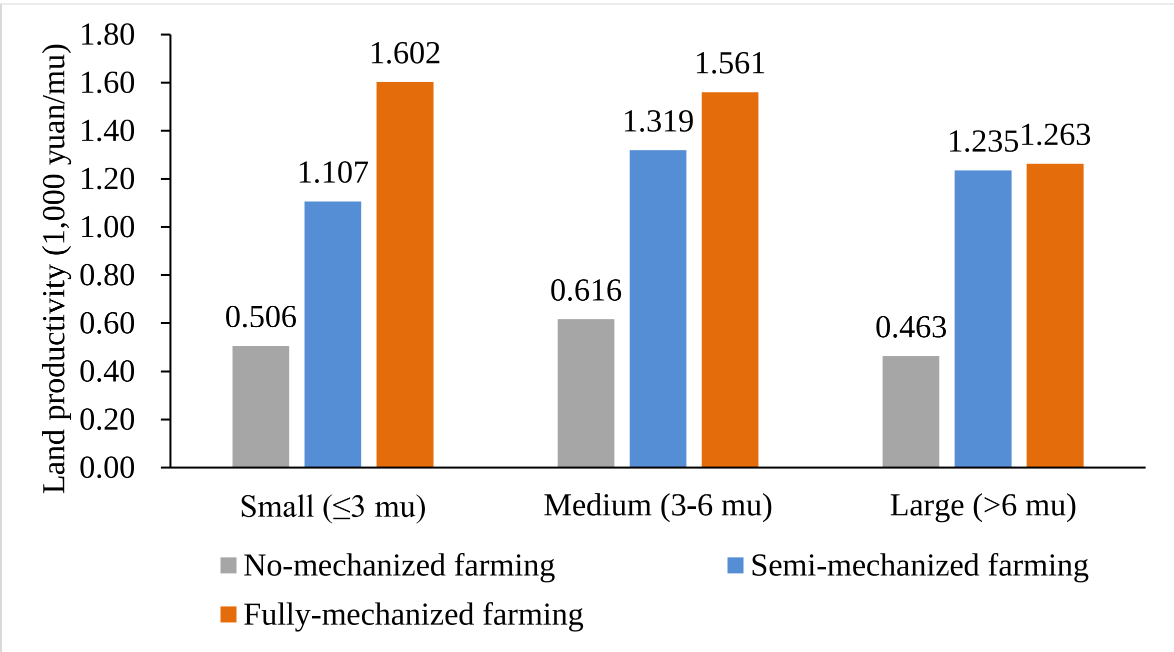

Figure 2 Relationship between agricultural mechanization and land productivity by farm size

Figure 3 shows the relationship between agricultural mechanization adoption and land productivity by geographic locations and shows that land productivity is the highest for no-mechanized farming adopters and full-mechanized farming adopters living in the eastern parts of China, and the land productivity is the highest for semi-mechanized farming adopters living in the central part of China. The information presented in Tables 1–3 suggests potential heterogeneous effects of agricultural mechanization adoption on land productivity between male and female-headed households, among farmers cultivating different farm sizes, and among those cultivating land in different geographic locations.

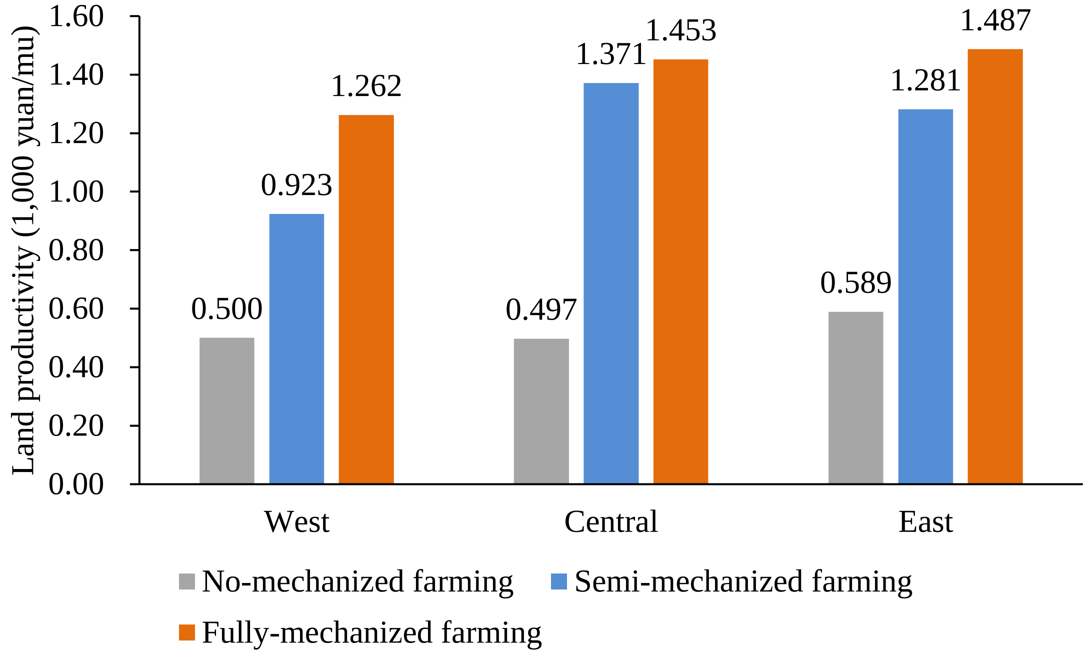

Figure 3 Relationship between agricultural mechanization and land productivity by regions

Table 2 presents the mean differences of the selected variables by agricultural mechanization adoption status. The last column of Table 2 reports the *F* value and the corresponding statistical significances that examine whether the means of the variables among the three mechanization strategies are the same. The results demonstrate that with changing agricultural production from no-mechanized farming to semi-mechanized farming and then to full-mechanized farming, the land productivity increase from 527 to 1,221 and then to 1,416 yuan/mu, respectively, and the group difference is significantly different at the 1% level. Compared with the no-mechanized farming adopters, the semi- and full-mechanized farming adopters are more educated and are more likely to receive an agricultural subsidy. We find that in the shift in agricultural production from no-mechanized to semi-mechanized and then to full-mechanized farming, the farm sizes monotonically increase from 5.17 to 7.73 and then to 10.17 mu, respectively. Generally, the results in Table 2 show that no-mechanized farming adopters, semi-mechanized farming adopters, and full-mechanized farming adopters are notably different in observed characteristics. The findings potentially indicate the presence of selection bias associated with the voluntary adoption of different agricultural mechanization strategies. Thus, a rigorous econometrics approach such as the MESR model should be estimated to analyze the unbiased effects of the adoption of three types of mechanization strategies on land productivity.

Table 2 Mean differences of the variables by agricultural mechanization status

Variables	No-mechanized farming	Semi-mechanized farming	Full-mechanized farming	F statistics
Land productivity	0.527 (1.719)	1.221 (1.838)	1.416 (2.094)	140.20***
Age	54.197 (15.066)	52.523 (13.120)	53.840 (12.683)	7.77***
Gender	0.602 (0.490)	0.602 (.4896875)	0.593 (0.492)	0.14
Education	2.427 (1.420)	2.557 (1.359)	2.562 (1.266)	6.95***
Off-farm work	0.494 (0.500)	0.479 (0.500)	0.455 (0.498)	2.47*
Household size	4.625 (2.196)	5.022 (2.318)	4.494 (2.024)	23.03***
Access to credit	0.331 (0.471)	0.347 (0.476)	0.312 (0.464)	1.65
Farm size	5.169 (6.721)	7.725 (8.284)	10.17 (10.50)	179.96***
Land use certificate	0.502 (0.500)	0.482 (0.500)	0.599 (0.490)	17.54***
Irrigation rate	0.473 (0.429)	0.495 (0.443)	0.402 (0.458)	13.54***
Subsidy	0.111 (0.701)	0.468 (0.708)	0.592 (1.106)	214.79***
Machinery service	0.238 (0.426)	0.343 (0.475)	0.312 (0.464)	35.22***
Library	0.749 (0.433)	0.793 (0.406)	0.795 (0.404)	8.24***
West	0.390 (0.488)	0.247 (0.431)	0.277 (0.448)	62.13***
Central	0.295 (0.456)	0.308 (0.462)	0.254 (0.435)	4.29**
East	0.314 (0.464)	0.445 (0.497)	0.469 (0.499)	65.92***

Note: Standard deviation is in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; F value shows the tests for differences across the three mechanization strategies.

4. Empirical results

4.1 Results of the MESR model estimation

4.1.1 Determinants of mechanization strategy adoption

Table 3 presents the results for the factors that affect farmers' decision to adopt different mechanization strategies, estimated using the MNL model and Equation (3). Because the magnitudes of the coefficients estimated from the MNL model are not straightforward, we calculate and present the marginal effects of the variables to provide a direct interpretation. In particular, the results presented in Columns 2, 3, and 4 show the significant variables that affect farmers' decision to adopt no-mechanized farming, semi-mechanized farming, and full-mechanized farming, respectively.

The marginal effects of the age variable are positive and statistically significant in the no-mechanized and full-mechanized farming specifications and negative and significant in the semi-mechanized farming specification. The findings suggest that a one-year increase in age increases the probabilities of adopting both no-mechanized farming and full-mechanized farming by 0.1%. On the one hand, elder household heads usually have extensive farming experience and farm management ability; thus, they are more favorable to cultivating farmland by relying on their experience rather than adopting modern technologies such as farm machines. On the other hand, elder farmers may have poorer health conditions than younger farmers; thus, they rely on farm machines to maintain or enhance land productivity (Zhang et al., 2019). Age decreases the likelihood of adopting semi-mechanized farming by 0.2%. The marginal effect of the gender variable in Column 2 of Table 3 is positive and statistically significant, and that in Column 4 is negative and significant. The findings suggest that male household heads are 1.9% more likely to adopt no-mechanized farming and their female counterparts are 2.0% more likely to adopt full-mechanized farming. When men stay at home, compared with women, they are less likely to adopt mechanized farming potentially because the household probably has no labor shortage. However, when male household heads migrate, women are more likely to adopt full-mechanized farming to maintain farm productivity and save farm labor time (e.g. the saved time can be used for other household activities such as child care (Kansanga et al., 2019; Ma et al., 2018b).

Table 3 Margins effects of the variables affecting adoption of agricultural mechanization strategies: First stage of MESR model estimates

Variables	No-mechanized farming	Semi-mechanized farming	Full-mechanized farming
Age	0.001 (0.000)***	-0.002 (0.000)***	0.001 (0.000)**
Gender	0.019 (0.010)*	0.000 (0.010)	-0.020 (0.009)**
Education	-0.005 (0.004)	-0.001 (0.003)	0.005 (0.003)
Off-farm work	0.010 (0.012)	-0.013 (0.010)	0.003 (0.009)
Household size	-0.006 (0.002)**	0.012 (0.002)***	-0.006 (0.002)***
Access to credit	-0.014 (0.012)	0.020 (0.011)*	-0.006 (0.009)
Farm size	-0.006 (0.001)***	0.002 (0.001)**	0.004 (0.001)***
Land use certificate	0.004 (0.012)	-0.031 (0.011)***	0.027 (0.008)***
Irrigation rate	-0.010 (0.014)	0.034 (0.011)***	-0.024 (0.010)**
Subsidy	-0.354 (0.064)***	0.227 (0.041)***	0.127 (0.023)***
Machinery service	-0.095 (0.011)***	0.069 (0.011)***	0.026 (0.008)***
Central	-0.005 (0.016)	0.033 (0.014)**	-0.027 (0.013)**
East	-0.140 (0.014)***	0.092 (0.013)***	0.049 (0.010)***
Library	-0.054 (0.014)***	0.024 (0.012)*	0.030 (0.010)***
Observations	3,964	1,577	906

Note: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The reference region is west.

We show that the marginal effects of the household size variable are negative and statistically significant in Columns 2 and 4 but positive and significant in Column 3. These findings suggest that a one-member increase in a household would decrease the probabilities of adopting both no-mechanized farming and full-mechanized farming by 0.6% but increase the likelihood of adopting semi-mechanized farming by 1.2%. To some extent, a larger household size means either a higher or a lower dependency ratio. On the one hand, households with a higher dependency ratio usually have capital constraints because of high living burdens in rural areas; thus, they may be unable to fully afford farm machines in agricultural production; on the other hand, a lower dependency ratio may indicate more labor endowments that can be allocated to income-generating off-farm activities, and this allows farm households to invest in farm machines or purchase machinery services. Access to the credit variable only has a significant impact on the choice of semi-mechanized farming. Our results show that households with credit access are 2.0% more likely to adopt semi-mechanized farming. Credit access helps release capital constraints of rural households and supports them to adopt farm machines in some production stages such as land ploughing. The finding is in line with the finding of Mottaleb et al. (2017), who showed that credit access promotes farmers' decisions to adopt machinery in Bangladesh.

The significant marginal effects of a land use certificate for semi- and full-mechanized farming adopters suggest that farm households with a land use certificate are 3.1% less likely to adopt semi-mechanized farming but 2.7% more likely to adopt full-mechanized farming. A land use certificate secures farmers' land use rights, enhancing the level of agricultural mechanization. A high irrigation rate tends to increase the probability of adopting semi-mechanized farming by 3.4% but reduces the likelihood of adopting full-mechanized farming by 2.4%. Agricultural subsidies play a critical role in promoting mechanization. Our results indicate that farm households receiving an agricultural subsidy are 22.7% and 12.7% more likely to adopt semi- and full-mechanized farming practices, respectively. The positive association between subsidy and mechanization has also been reported in other studies (Benin et al., 2013; Diao et al., 2014). Consistent with the findings in the literature (Van Loon et al., 2020; Wang et al., 2016a), our results indicate that access to a machinery service promotes agricultural mechanization. In particular, we show that farm households who have access to a machinery service provided by the village committee are 6.9% and 2.6% more likely to adopt semi- and full-mechanized farming, respectively.

Compared with farmers residing in the western part of China (reference division), their counterparts living in the central part of China are 3.3% more likely to adopt semi-mechanized farming but 2.7% less likely to adopt full-mechanized farming. Relative to farmers in western China, those in eastern China are 9.2% and 4.9% more likely to adopt semi- and full-mechanized farming practices, respectively. These findings suggest that location-fixed effects also influence farmers' decisions to mechanize agriculture. Finally, the positive and statistically significant marginal effects of the library variable indicate that the existence of a library in a village increases farmers' probabilities to adopt semi- and full-mechanized farming practices. Because the library variable serves as an instrumental variable in this study, we expect it has a nonsignificant impact on land productivity.

4.1.2 Determinants of land productivity

The estimates for the factors that affect the land productivity of no-mechanized farming adopters, semi-mechanized farming adopters, and full-mechanized farming adopters are respectively presented in Columns 2, 3, and 4 of Table 4. Our results show that the coefficients of the age variable are negative and statistically significant in Columns 2 and 3, suggesting that elder household heads adopting both no-mechanized farming and semi-mechanized farming obtain lower land productivity. Compared with younger farmers, elder farmers usually have poorer health and few advanced production skills, which constrain their benefits from agricultural production. The coefficient of the gender variable is positive and statistically significant in Column 2 of Table 4, but negative and significant in Column 3. The findings suggest that relative to female household heads, male household heads obtain higher land productivity through adopting no-mechanized farming but lower land productivity by adopting semi-mechanized farming. Male household heads traditionally dominate agricultural production. In female-dominated households, farm machines enable and empower rural women to obtain higher land productivity (Fischer et al., 2018). The negative and significant coefficients of the off-farm work variable in both the no-mechanized and full-mechanized farming specifications suggest that off-farm work participation decreases land productivity. The findings are in line with the so-called lost labor effect (Feng et al., 2010). That is, allocating more labor time to off-farm work would reduce the time allocated to farm work, which reduces farm economic performance.

The coefficients of the household size variable are positive and statistically significant in the no-mechanized farming specification but negative and significant in the semi-mechanized farming specification. The findings suggest that larger households adopting no-mechanized farming obtain higher land productivity, a finding that highlights the positive relationship between farm labor use and land productivity. The adoption of semi-mechanized farming means that farm machines are adopted in some production stages; however, this practice may reduce land productivity if labor and farm machines are misallocated.

The coefficient of the farm size variable is negative and statistically different from 0 in the semi-mechanized farming specification. This finding suggests that households cultivating a larger farm size tend to obtain lower land productivity. The finding of the inverse farm size-productivity relationship is supported by the findings in the literature (Kagin et al., 2016; Newman et al., 2015). The significant and statistically significant coefficient of the land use certificate variable in Column 3 suggests that a land use certificate contributes to an increase in land productivity. This finding is consistent with the finding of Deininger and Jin (2009), who found that better-enforced tenure of land use security increases farmers' incentives to invest in productivity-increasing inputs (e.g. fertilizers, pesticides, and improved seeds) to obtain higher land productivity. Irrigation rate is observed to have a positive and significant impact on land productivity for both no-mechanized and full-mechanized farming adopters, a finding echoed by Chaudhry and Barbier (2013). Access to irrigation increases the absorption of farm inputs such as fertilizers, contributing to an increase in land productivity.

The subsidy variable appears to have a positive and significant impact on the land productivity of no-mechanized farming adopters. In their study on Nigeria, Wossen et al. (2017) also showed that the implementation of a mobile phone-based input subsidy program initiated in Nigeria, which provided fertilizer and improved seed subsidies through electronic vouchers, increases land productivity in maize production. The differences in land productivity also exist among different survey regions. We show that relative to farmers in the western part of China, no-mechanized farming adopters in eastern China obtain higher land productivity, whereas semi-mechanized farming adopters in both central and eastern China obtain higher land productivity. The findings suggest location-based heterogeneities (e.g. differences in climate conditions, soil quality, and institutional arrangement) that may also influence land productivity.

The lower parts of Table 4 present the coefficients of the selectivity correction terms. We show that the coefficients of λ_2 and λ_3 in Column 2 of Table 4 are statistically significant, suggesting the presence of unobservable selection bias (Di Falco and Veronesi, 2013; Khonje et al., 2018; Vigani and Kathage, 2019). Thus, the MESR approach is preferred to estimate the impacts of the adoption of different mechanization strategies on land productivity because, in essence, it enables us to address the selection bias issue arising from the observed and unobserved characteristics.

4.1.3 ATT estimations

The analyses presented in Sections 4.1.1 and 4.1.2 enable us to better understand the factors that affect farmers' decisions to adopt different types of mechanization strategies and the factors that influence land productivity. To understand the effects of the adoption of different agricultural mechanization strategies on land productivity, we further calculated the average ATT by using Equation (7). These ATT estimates take into account both observable and unobservable selection bias.

The ATT results, presented in Table 5, reveal that the adoption of both semi-mechanized and full-mechanized farming increases land productivity. In particular, we show that the adoption of semi-mechanized farming increases land productivity by 60%, and the adoption of full-mechanized farming tends to increase land productivity by 82%.[3] Our ATT results in Table 5 also show that relative to the adoption of semi-mechanized farming, the adoption of full-mechanized farming has a larger effect on land productivity. The use of machines on farms relaxes peak-season labor constraints and enhances farm efficiency, contributing to an improvement in land productivity. A positive relationship between agricultural mechanization and land productivity has also been found by Ma et al. (2018b) for China and Paudel et al. (2019) for Nepal.

[3] Here, we show that agricultural mechanization increases land productivity. To identify whether farmers with higher land productivity are more likely to be those adopting mechanized farming, by referring to Vigani and Kathage (2019), we used the Hausman test to examine the reverse causality between agricultural mechanization and land productivity. First, we estimate Equation (4) using the OLS regression model and calculate the residual. Next, we estimate Equation (1) using an MNL model that includes the residual predicted from the first stage as a regressor. The *t* test of residual variable is not statistically significant (*p*-value=0.683). Hence, we conclude that there is no reverse causality between agricultural mechanization and land productivity.

Tables 4 Determinants of land productivity by mechanization status: Second stage of the MESR model estimates

Variables	Dependent variable = Land productivity		
	No-mechanized farming	Semi-mechanized farming	Full-mechanized farming
Age	-0.025 (0.007)***	-0.012 (0.006)*	-0.016 (0.010)
Gender	0.198 (0.119)*	-0.182 (0.110)*	0.217 (0.183)
Education	-0.004 (0.042)	0.021 (0.041)	-0.047 (0.057)
Off-farm work	-0.271 (0.110)**	-0.095 (0.111)	-0.497 (0.185)***
Household size	0.129 (0.052)**	-0.079 (0.042)*	-0.039 (0.061)
Access to credit	0.213 (0.135)	-0.074 (0.104)	-0.132 (0.154)
Farm size	-0.008 (0.010)	-0.021 (0.013)*	-0.013 (0.013)
Land use certificate	-0.156 (0.130)	0.354 (0.147)**	0.283 (0.236)
Irrigation rate	0.464 (0.187)**	0.165 (0.159)	0.589 (0.215)***
Subsidy	2.724 (0.663)***	-0.053 (0.132)	0.021 (0.125)
Machinery service	0.774 (0.187)***	-0.111 (0.111)	-0.188 (0.168)
Central	0.286 (0.196)	0.540 (0.183)***	0.089 (0.262)
East	0.769 (0.216)***	0.281 (0.157)*	-0.025 (0.232)
σ^2	39.851 (26.106)	3.370 (2.404)	6.428 (4.039)
λ_1		0.229 (0.365)	0.434 (0.267)
λ_2	1.156 (0.208)***		-0.707 (0.483)
λ_3	-0.855 (0.303)***	-0.179 (0.595)	
Constant	2.122 (0.507)***	2.259 (0.549)***	1.367 (1.630)
Observations	3,964	1,577	906

Note: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The reference region is west.

Table 5 Results of the treatment effects estimations

Mechanization strategies	Mean land productivity		ATT	*t*-value	Change (%)
	Adopters	Non-adopters			
Semi-mechanized farming	1.221 (0.010)	0.762 (0.009)	0.459 (0.010)***	45.463	60.236
Full-mechanized farming	1.416 (0.018)	0.779 (0.015)	0.637 (0.019)***	34.147	81.772

Note: Standard errors are in parentheses; *** $p < 0.01$; Land productivity is measured at 1,000 yuan/mu; The values of land productivity for adopters are estimated by using Equation (6a) in an observed context, and the values of land productivity for non-adopters are estimated by using Equation (6b) in a counterfactual context.

Figure 4 illustrates the kernel densities of predicted land productivity distributions by mechanization adoption status. The figure shows that the kernel density of land productivity for both semi- and full-mechanized farming adopters is further to the right than that for no-mechanized farming adopters. The findings further demonstrate that agricultural mechanization increases land productivity, and farmers adopting full-mechanized farming tend to benefit more than their counterparts adopting semi-mechanized farming.

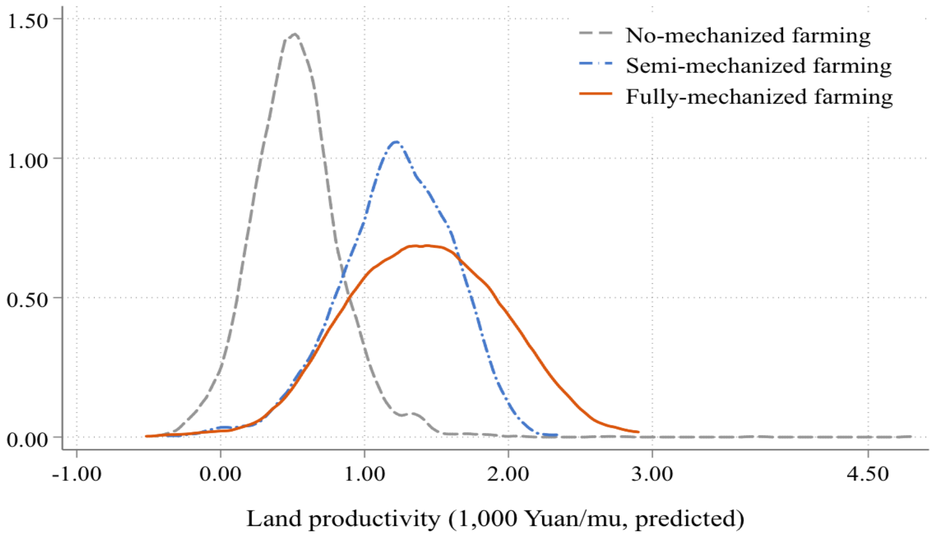

Figure 4 Kernel density distribution of land productivity by agricultural mechanization status

4.2 Heterogeneous effects estimations

The information presented in Figures 1–3 suggests that land productivity for no-mechanized farming adopters, semi-mechanized farming adopters, and full-mechanized farming adopters are different in gender, farm size, and geographic location. Here, we empirically test the heterogeneous effects of agricultural mechanization adoption to improve our understanding.

The upper parts of Table 6 show the results of the heterogeneous effects estimations by gender. The results show that relative to female-headed households adopting semi-mechanized farming, male-headed households adopting the same mechanization strategy obtain lower land productivity. For male and female-headed households, the adoption of semi-mechanized farming increases land productivity by 33% and 109%, respectively. Regarding the adoption of full-mechanized farming, male-headed households perform physically better than their female-headed counterparts, but the female-headed households obtain a higher increment in land productivity changes. We show that the adoption of full-mechanized farming increases land productivity by 79% for male-headed households, and it increases land productivity by 109% for female-headed households. Our findings are well in line with the literature of agricultural feminization and women empowerment of agricultural mechanization (de Brauw et al., 2013; Mukhamedova and Wegerich, 2018).

The middle parts of Table 6 show the results of the heterogeneous effects estimations by farm size. With increasing farm sizes from small (≤ 3 mu) to medium (3–6 mu) and then to large (>6 mu), land productivity for semi-mechanized farming adopters is monotonically increasing, whereas that for full-mechanized farming adopters exerts a U-shaped relationship between farm size and land productivity changes. For example, when switching farm sizes from small to medium and then to large, the treatment effects of the adoption of full-mechanized farming on land productivity decrease from 212% to 154% and then increase to 177%, respectively. This finding is largely consistent with the argumentation in Kagin et al. (2016), who stated that farmers cultivating small farms in Mexico are more likely to operate closer to their technical efficiency frontier than large farms are. Given this reason, small farms intend to obtain high land productivity.

The lower parts of Table 6 present the results of the estimation of the heterogeneous effects by geographic locations. Our results reveal that among the farm households located in western, central, and eastern China, those cultivating land in central China obtains the highest land productivity by adopting semi-mechanized farming or full-mechanized farming. This difference can be partially explained by the favorable agricultural production conditions (e.g. better natural resources, climate conditions, and appropriate typography for machine use) in central China, the major grain-producing region.

4.3 Robustness check

For the robustness check, we also estimate the impact of the adoption of different agricultural mechanization strategies on land productivity by using the MVTE model. The results, presented in Table A1 in the Appendix, show that shifting from the adoption of no-merchanded farming to the adoption of semi-mechanized and full-mechanized farming increases land productivity significantly, which further confirms the positive association between agricultural mechanization and land productivity. However, our results indicate that the MVTE model tends to overestimate the treatment effects of agricultural mechanization adoption. In particular, the ATT estimates in the MVTE model show that the adoption of semi-mechanized farming and adoption of full-mechanized farming increase land productivity by 113% and 167%, respectively, and the values are 60% and 82% in Table 5. The findings are not implausible because the MVTE model cannot mitigate the selection bias from unobserved factors (e.g. farmers' innate abilities and motivation to mechanize agriculture) (Linden et al., 2016; Ma et al., 2018a), and the findings of the significant selectivity correction terms (λ_2 and λ_3) in Column 2 of Table 4 suggest the presence of selection bias from unobserved factors.

Table 6 Results of the heterogeneous effects estimations

	Mechanization strategy	Mean land productivity		ATT	*t*-value	Change (%)
		Adopters	Non-adopters			
Disaggregated analyses by gender						
Male	Semi-mechanized	1.146 (0.014)	0.864 (0.011)	0.282 (0.013)***	21.954	32.639
	Full-mechanized	1.525 (0.063)	0.854 (0.031)	0.671 (0.025)***	27.400	78.571
Female	Semi-mechanized	1.333 (0.015)	0.637 (0.015)	0.696 (0.018)***	37.769	109.262
	Full-mechanized	1.257 (0.026)	0.668 (0.022)	0.589 (0.035)***	16.624	88.174
Disaggregated analyses by farm size						
Small (≤3 mu)	Semi-mechanized	1.107 (0.002)	0.516 (0.002)	0.591 (0.004)***	132.243	114.535
	Full-mechanized	1.602 (0.120)	0.513 (0.034)	1.089 (0.002)***	605.239	212.281
Medium (3–6 mu)	Semi-mechanized	1.319 (0.000)	0.613 (0.002)	0.707 (0.002)***	451.139	115.334
	Full-mechanized	1.561 (0.006)	0.615 (0.002)	0.946 (0.003)***	286.077	153.821
Large (>6 mu)	Semi-mechanized	1.235 (0.008)	0.460 (0.001)	0.775 (0.007)***	109.612	168.478
	Full-mechanized	1.263 (0.003)	0.456 (0.002)	0.807 (0.002)***	451.753	176.974
Disaggregated analyses by geographic locations						
West	Semi-mechanized	0.923 (0.025)	0.649 (0.023)	0.274 (0.023)***	11.791	42.219

	Full-mechanized	1.262 (0.063)	0.506 (0.031)	0.756 (0.052)***	14.674	149.407
Central	Semi-mechanized	1.371 (0.016)	0.540 (0.031)	0.831 (0.030)***	27.389	153.889
	Full-mechanized	1.453 (0.039)	0.496 (0.040)	0.957 (0.047)***	20.287	192.944
East	Semi-mechanized	1.281 (0.019)	1.103 (0.022)	0.178 (0.020)***	8.981	16.138
	Full-mechanized	1.487 (0.023)	1.178 (0.033)	0.309 (0.039)***	7.883	26.231

Note: Standard errors are in parentheses; *** $p < 0.01$; Land productivity is measured at 1,000 yuan/mu; The values of land productivity for adopters are estimated by using Equation (6a) in an observed context, and the values of land productivity for non-adopters are estimated by using Equation (6b) in a counterfactual context.

5. Conclusions

Although several studies have demonstrated the importance of agricultural mechanization in boosting farm economic performance and rural development, no other studies have considered how the adoption of different mechanization strategies affects land productivity. In response to this gap, this study investigated the determinants and impacts of the adoption of no-mechanized farming, semi-mechanized farming, and full-mechanized farming on land productivity. The MESR model was used to address the self-selection issue associated with farm machine use and analyze nationally representative data derived from the 2016 CLDS.

The results of the first stage estimation of the MESR model show that age, household size, farm size, land use certificate, irrigation rate, subsidies, and machinery service are major factors that affect farmers' decision to adopt semi-mechanized and full-mechanized farming practices. In addition, our results estimated from the second stage of the MESR model suggest that a land use certificate, irrigation rate, and agricultural subsidies are the major factors that positively determine land productivity.

Our results indicated the presence of an unobserved selection bias issue. After controlling for the selection bias, we provided evidence that the adoption of both semi- and full-mechanized farming practices increases land productivity. Specifically, our treatment effects estimates show that the adoption of semi-mechanized farming increases land productivity by 60%, and the adoption of full-mechanized agriculture increases land productivity by 82%. The disaggregated analyses show that female-headed households adopting semi-mechanized farming obtain higher land productivity than their male-headed counterparts who adopt the same mechanization strategy, and male-headed households adopting full-mechanized farming perform better than their female-headed counterparts. There is a positive relationship between farm size and land productivity for semi-mechanized farming adopters, but that relationship is negative for adopters of full-mechanization farming. Semi- and full-mechanized farming adopters living in central China obtain higher land productivity relative to their counterparts residing in western and eastern China.

Our findings have important implications for sustainable agricultural production and food security. The finding that agricultural mechanization increases land productivity suggests that encouraging smallholder farmers to adopt machines on their farms can facilitate sustainable production and ensure food security. Small farm size and land fragmentation have been identified as two major obstacles to agricultural mechanization in rural China (Wang et al., 2018). In this study, we also show that farm size is also a critical driver of agricultural mechanization. Thus, the government should support the development of scale-appropriate mechanization. Additionally, rural development programmed that target sustainable land use should consider consolidating plots to form a larger operational plot, and further developing family farms through land transfer would result in any observable difference. The positive and statistically significant impacts of variables including access to credit, a subsidy, and a machinery service on the adoption of semi- and full-mechanized farming suggest that government efforts that relax farm households' financial constraints through improving rural households' access to credit provide agricultural subsidies and facilitate the development of machinery service markets at the regional levels could enhance farmers' adoption of agricultural machines, which would increase land productivity and food security.

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Appendix A

Table A1 ATT estimates the impact of agricultural mechanization adoption on land productivity: MVTE model estimates

Outcomes	Mechanization strategy	ATT	z-value	Change (%)
Land productivity	From no-mechanized farming to semi-mechanized farming	0.647 (0.057)***	11.36	112.730
Land productivity	From no-mechanized farming to full-mechanized	0.958 (0.096)***	9.93	167.018

Note: Standard errors are in parentheses; *** $p < 0.01$; The reference mechanization strategy is no-mechanized farming; Land productivity is measured at 1,000 yuan/mu; The ATT estimates of MVTE model are calculated using the inverse-probability- weighted regression-adjustment estimator.