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Factors Influencing the Adoption of Agricultural Machinery by Chinese Maize Farmers

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Abstract: As the major labor force has shifted from rural areas to cities, labor shortages in agricultural production have resulted. In the context of technical progress impact, and depending on farm resource endowments, farmers will choose effective labor saving technology such as machinery to substitute for the missing manual labor. The reasons behind farmers' adoption of machinery technology are worth exploring. Therefore, this study uses 4165 Chinese maize farmers as the target group. Multivariate probit models were performed to identify the factors that affect maize farmers' adoption of four machinery technologies as well as the interrelation between these adoption decisions. The empirical results indicate that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields in the farm has a negative impact. Maize farmers in the Northeast and North have higher machinery adoption odds than other regions. The adoption of these four machinery technologies are interrelated and complementary. Finally, moderate scale production, crop diversification, subsidizing agricultural machinery and its extension education, and land consolidation, are given as recommendations for promoting the adoption of agricultural machinery by Chinese maize farmers.

Keywords: agricultural machinery; China; maize production; technology adoption

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1. Introduction

As agricultural mechanization develops, farm machinery is gradually playing an important role in replacing manual labor and draft animals (e.g., horses, oxen, mules) and improving agricultural productivity. The economic benefits of machinery use, however, depend highly on economies of scale [1–3]. Farmers can use agricultural machinery by purchasing, renting, or buying machinery services [4]. China, known as the second largest maize producer in the world [5], has adopted agricultural machinery in plowing, seeding, and harvesting for a long time. Figure 1 indicates the growth trend of mechanization in China's maize production at the national level. Mechanical plowing and mechanical seeding are well developed, while mechanical harvesting lags a little behind compared with them. In 2018, the average maize comprehensive mechanization rate was 88.31% in all production regions of China [6].

Several studies have analyzed the factors influencing the adoption of agricultural machinery by Chinese maize farmers [4,7–11] (Table 1). These factors mainly include three aspects: farmer features (e.g., age, gender, education level, farming experience, off-farm employment, etc.), farm characteristics (e.g., farm size, location, soil fertility, etc.), and social facilitating conditions (e.g., subsidies, extension services, farmer organizations, etc.). Probit models, multivariable probit models, and other econometric models were performed to analyze the quantitative relations between these factors and farmers' adoption decisions.

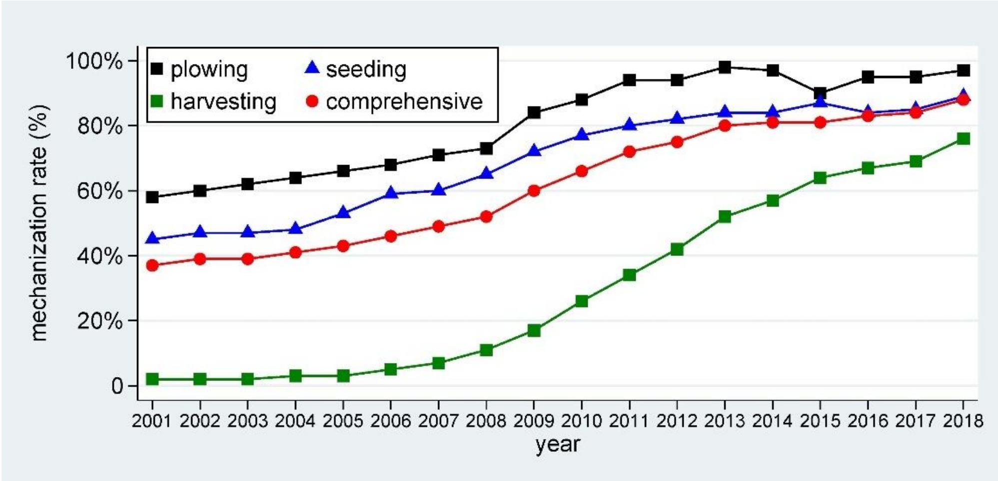

Figure 1. Mechanization rate of maize production in China, 2001–2018. Data source: China Agricultural Machinery Industry Yearbook [6]. Note: mechanical plowing rate—areas of mechanical plowing (hm^2)/areas that are supposed to be plowed (hm^2); mechanical seeding rate—areas of mechanical seeding (hm^2)/total areas of sowing (hm^2); mechanical harvesting rate—areas of mechanical harvesting (hm^2)/total areas of sowing (hm^2); comprehensive mechanization rate—0.4 × mechanical plowing rate + 0.3 × mechanical seeding rate + 0.3 × mechanical harvesting rate.

Table 1. The research of agricultural technology adoption: a review.

Agricultural Technology	Country	Target Group	Method of Analysis	Factors Affect the Adoption	References
Rotary cultivator for plowing	China	Maize farmers	A control function approach with an instrumental variable	Education (−), Household size (−), Extension contact (+), Transportation condition (+), Access to credit (+), Irrigation (+), Farm size (+), Pesticide costs (+), Fertilizer costs (+), Seed costs (−)	[11]
Several farm machines which can be used in maize production and postharvest management	China	Maize farmers	Bivariate ordered probit model and endogeneity-corrected ordinary least square regression model	Gender (−), Household size (−), Farm size (+), Soil fertility (+), Subsidy (+)	[4]
Mechanization services	China	Maize farmers	Multivariable probit model	Number of family members, Number of parcels, The distance to township, Off-farm employment (+), Age (+)	[9]
Total machinery horsepower used in plowing, sowing, and harvesting	China	Wheat farmers and maize farmers.	Ordinary least squares (OLS) with instrumental variables (IV)	Land fragmentation (−), Total operating area (+), Machinery price (−),	[7]
Agricultural machines for pesticide application	China	Maize farmers	Endogenous switching regression model	Gender (−), Risk preference (−), Transportation condition (+), Subsidy (+), Extension contact (+)	[10]
Three soil conservation practices	Spain	Olive farmers	Multivariate probit model	Olive grove area (+), Family labor force (−), Belong to an irrigation district (+), Farm profitability (+)	[12]
Conservation tillage, compost, and chemical fertilizer	Ethiopia	Wheat farmers, barley farmers, and teff farmers	Trivariate probit model	Male (+), Age (−), Labor (+), Extension (+), Farmer organizations (+), Farm size (+), Plot ownership (+), Plot slope (−)	[13]

Note: In column 5, the effects of factors are shown in the brackets. "+" means a positive effect and "−" means a negative effect.

Specifically, Zhou et al. [11] estimated the impacts of farm machinery use on maize yields by using a control function approach. In the first stage, smartphone use was employed as an instrumental variable in the farm machinery adoption equation; in the second stage, the inverse mills ratio estimated from the first stage was added to the maize production function as an extra regressor to correct the endogeneity issue caused by selection bias in farm machinery adoption. The results indicated that farmers' educational level, household size, extension service, transportation convenience of farm, farm size, and production inputs (e.g., pesticides, fertilizers, and seeds) are the main factors that affect farmers' adoption of machinery in maize production. Ma et al. [4] used a bivariate ordered probit model with an instrumental variable (whether or not receiving a machinery purchasing subsidy) to estimate farmers' adoption of farm machinery in the first step. In the second step, endogeneity-corrected ordinary least square regression models were performed to test the effect of machinery use on maize yields and agricultural expenses. The empirical results indicate that off-farm employment, farm size, and subsidy had positive impacts on machinery adoption. Yi et al. [9] estimated 600 maize farmers' adoption of agricultural mechanization services in seven regions of China with a multivariable probit model. To overcome the endogeneity of off-farm employment on the adoption of agricultural mechanization services, the average wage of off-farm work was used as an instrumental variable in the adoption equation. The results showed that both population aging and off-farm employment contributed positively to farmers' adoption of agricultural mechanization services. Zhang et al. [10] used an endogenous switching regression model to simultaneously identify the factors influencing the adoption of farm machines in pesticide application and the impact of this adoption on pesticide expenditures. The mechanical pesticide spraying rate in each village was used as an instrumental variable in the farm machine selection equation to overcome the endogeneity of adoption decision caused by observed and unobserved factors. This study shows off-farm employment and farm size would positively affect farmers' decision to use farm machines in pesticide application. Similarly, these abovementioned studies solved model endogeneity issues by using instrumental variables. However, it is tricky sometimes to find appropriate instrumental variables.

In addition to research on machinery technology adoption among Chinese farmers, there are also some papers addressing the adoption of other agricultural technologies such as conservation and sustainable agriculture practices around the world [12,13] (Table 1). Rodríguez-Entrena et al. [12] used a trivariate probit model to identify the determinants in the adoption of three soil conservation practices in Spanish olive production. Their results suggest that the farmers' decision to adopt a practice is correlated with other practices and that the adoption of one practice could promote the adoption of others.

A number of papers only study farmers' adoption of one particular technology or a set of technologies and thus have biased results caused by ignoring the interrelation from the adoption of different technologies [4,7,10,11]. Zhou et al. [11] only studied the adoption of the rotary cultivator for plowing in maize production among 493 farmers in Gansu, Henan, and Shandong provinces. Ma et al. [4] investigated the adoption of machinery in 12 maize production stages among 493 farmers in three provinces of China by using a bivariate ordered probit model, but failed to consider the potential interrelation from the adoption of different technologies. Moreover, most of the existing research on Chinese maize farmers' machinery adoption is only focused on some specific regions with limited samples [4,7,9–11]. Nationwide maize farmers' machinery adoption research is still missing in China.

The contributions of this paper are threefold: firstly, this is the first research to use nationwide data to study Chinese maize farmers' machinery adoption. The databases include 4165 maize farmers across six agroecological maize regions of China: Southwest, Northeast, North, Yellow-Huai River Valley, Northwest, and South. These samples are comprehensive and sufficient to represent most of the maize farmers in China. And the regional differences in machinery adoption were compared in six agroecological maize regions. Secondly, in order to obtain a good understanding of maize farmers' machinery adoption decisions, we investigated their adoption of machinery technologies in four key production processes: seeding, plowing, harvesting, and pesticide spraying. Thirdly, given the potential interrelation among these adoption decisions, multivariate models were performed to study the factors that influence the adoption of these machinery technologies. The aims of this paper are: (i) to identify the factors that influence the adoption of four machinery technologies by Chinese maize farmers; (ii) to explore the correlations among the adoption decisions of these four machinery technologies; and (iii) to provide some policy implications based on these conclusions to promote the use of agricultural machinery by Chinese maize farmers.

2. Materials and Methods

2.1. Data Source

This study uses data from the 2017 Chinese Family Database (CFD) of Zhejiang University, and from the 2017 China Household Finance Survey (CHFS) conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics (China). These databases contain 5979 households who produced maize as one of the main crops on their farm. After data cleaning, 669 outliers were removed if they had have zero agricultural output values or where the areas of mechanical operation in their farm were larger than the farm size itself. After 1145 observations with missing values were removed, only 4165 valid maize farmers across 24 provinces were left.

2.2. Research Study Design

The 2017 CFD and 2017 CHFS are national representative surveys conducted in 2016, including more than 40,000 households across 29 provinces in the mainland of China. The survey adopted stratified three-stage sampling: county level, village level, and household level. Samples were selected randomly in each stage.

The questionnaire includes household demographic characteristics, family assets, agricultural production, family incomes and expenditures, etc. Since this study wants to explore the factors that influence the adoption of four machinery technologies in maize production, some explanatory variables and four dependent variables were selected from the databases (Table 2).

Table 2. Descriptive statistics of variables.

Variables	Definitions	Mean	Std. Dev.
Dependent variables			
Mechanical plowing	1 if the farm used machines for plowing in maize production; 0 otherwise	0.580	0.494
Mechanical seeding	1 if the farm used machines for seeding in maize production; 0 otherwise	0.439	0.496
Mechanical harvesting	1 if the farm used machines for harvesting in maize production; 0 otherwise	0.467	0.499
Mechanical spraying	1 if the farm used machines for pesticide spraying in maize production; 0 otherwise	0.178	0.383
Explanatory variables			
Maize sowing area	Total areas of maize growing in the farm (mu)	6.487	12.650
Number of discrete fields in the farm	Number of discrete fields in the farm used for agricultural production	5.754	6.157
Arable land area	Total areas of arable land in the farm (mu)	10.001	19.446
Crop diversity	Number of crops produced on the farm	2.727	1.648
Family labor	Number of people participating in agricultural production in the family	1.961	0.822
Subsidy	1 if the farm received a subsidy to support agricultural production; 0 otherwise	0.763	0.425
Technical assistance	1 if the farm received technical assistance for agricultural production; 0 otherwise	0.100	0.300
Economies of scale	Total value of agricultural output by the farm (unit: 1000 yuan)	12.907	36.084

Table 2. *Cont.*

Variables	Definitions	Mean	Std. Dev.
Southwest	1 if the farm is located in Sichuan, Chongqing, Guizhou, or Yunnan; 0 otherwise	0.248	0.432
Northeast	1 if the farm is located in Liaoning, Jilin, or Heilongjiang; 0 otherwise	0.181	0.385
North	1 if the farm is located in Beijing, Tianjin, Hebei, or Inner Mongolia; 0 otherwise	0.128	0.334
Yellow-Huai River Valley	1 if the farm is located in Shanxi, Shandong, Henan, Shaanxi, Anhui, or Jiangsu; 0 otherwise	0.299	0.458
Northwest	1 if the farm is located in Gansu or Ningxia; 0 otherwise	0.055	0.228
South	1 if the farm is located in Guangxi, Hainan, Hunan, Hubei, or Zhejiang; 0 otherwise	0.089	0.285
Number of observations	4165		

To compare regional heterogeneity, farm households were grouped together based on agroecological maize regions in China [14] (Figure 2): 1032 farms (24.78%), 754 farms (18.10%), 533 farms (12.80%), 1247 farms (29.94%), 229 farms (5.50%), and 370 farms (8.88%) are located in the Southwest, Northeast, North, Yellow-Huai River Valley, Northwest, and South respectively.

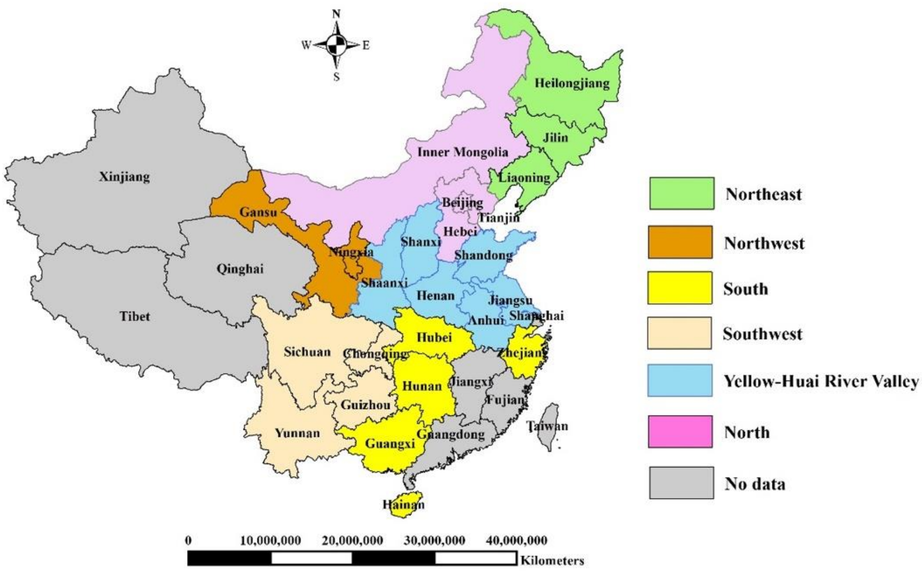

Figure 2. The division of six agroecological maize regions in this study.

2.3. Theoretical Framework

Given that the adoption of the four machinery technologies in this study is not mutually exclusive, the adoption of one technology could affect the adoption of others. Failure to consider the correlation among adoption decisions regarding different technologies will cause biased results [12,13]. Therefore, univariate probit or logit models are not sufficient for use in modeling the adoption of several interrelated technologies because they estimate the adoption of each technology independently, which ignores the correlations among these adoption decisions. The multivariate probit (MVP) model could overcome this problem. MVP models not only estimate the influence of a set of independent variables on the adoption of each of the different technologies but also account for the interdependence among these simultaneous adoption decisions [12,13]. Hence, the MVP model was chosen for this study.

The MVP model is specified as follows [15]:

$$Y_{ij}^{*} = \beta_j X_{ij} + \varepsilon_{ij}\ ,\ (\mathrm{j} = 1,\ 2,\ 3,\ 4) \tag{1}$$

$$Y_{ij} = \begin{cases} 1,\ if\ Y_{ij}^{*}\ 0 \\ 0,\ if\ Y_{ij}^{*}\ \leq\ 0 \end{cases} \tag{2}$$

where j = 1, 2, 3, 4 denotes mechanical plowing, mechanical seeding, mechanical harvesting, and mechanical spraying. Y_{ij}^{*} is a latent variable of the rational i^{th} farmer, which captures the unobserved preferences or demand associated with the j^{th} choice of machinery technologies. β_j is the coefficient to be estimated by a simulated maximum likelihood procedure. X_{ij} is the vector which represents the factors that affect the adoption of machinery. Given the nature of the latent variable, Y_{ij}^{*} is estimated by the observable dichotomous variable Y_{ij}. ε_{ij} is the stochastic error term following a multivariate normal distribution (MVN):

$$(\varepsilon_{i1}\ ,\ \varepsilon_{i2},\ \varepsilon_{i3},\ \varepsilon_{i4})'\ \sim\ \mathrm{MVN}\left(0,\ \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 \end{bmatrix}\right) \tag{3}$$

where ρ_{jk} is the correlation coefficient of ε_j and ε_k (j $\neq$ k). This assumption with non-zero off-diagonal allows the correlation of error terms among these four adoption equations. If $\rho_{jk} > 0$, the adoptions of these two technologies are complementary; if $\rho_{jk} < 0$, the adoptions of these two technologies are substitutable [12].

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 presents the description of variables used in the empirical analysis. The average maize sowing area of each farm is 6.49 mu. On average, each farm has five discrete fields and arable land areas of 10 mu. Most of the farmers produce 2 to 3 crops on the farm, while an average of only 1 to 2 family members participated in agricultural production. A total of 76.3% of farmers had received subsidy from the government to support agricultural production. Only 10% of farmers received technical assistance in agricultural production. Economies of scale averaged 12,907.27 yuan, from a minimum of 60 yuan to a maximum of 1567,400 yuan.

Table 3 shows the adoption rates of four agricultural machinery technologies in six agroecological maize regions. The adoption rates are differentiated by technology and region. Compared with other regions, the Northeast has the highest average adoption rate while the South has the lowest. The overall mechanical plowing adoption rate is 58.01% across six regions, while mechanical spraying is only 17.82%.

Table 3. Adoption rates of four agricultural machinery technologies in six agroecological maize regions and the overall adoption rates (%).

	Adoption Rates of Machinery Technologies in Six Agroecological Maize Regions						**Overall**
	Southwest	**Northeast**	**North**	**Yellow-Huai River Valley**	**Northwest**	**South**	
Mechanical plowing	13.74%	22.43%	16.80%	35.10%	6.66%	5.26%	58.01%
Mechanical seeding	2.13%	25.45%	21.46%	42.42%	7.17%	1.37%	43.87%
Mechanical harvesting	10.84%	20.85%	18.13%	38.42%	5.75%	6.01%	46.75%
Mechanical spraying	6.74%	48.92%	13.21%	24.53%	4.45%	2.16%	17.82%

3.2. Empirical Results

Table 4 shows the correlation coefficients of the machinery technology adoption equations. The likelihood ratio (LR) test is significant (χ^2 (6) = 1772.26***, H_0 is rejected), which suggests the joint significance of the error correlations. This supports the idea that using MVP models is more efficient than univariate models. All the error correlation coefficients are positive and significantly different from zero. This result indicates the interdependence among the adoption decisions of different machinery technologies. More specifically, the adoptions of these four machinery technologies are complementary. The adoption of one machinery technology could promote the adoption of other machinery technologies.

Table 4. Correlation coefficients of machinery technology adoption equations.

		ρ	Std. Err.
Mechanical seeding vs. Mechanical plowing	ρ_{21}	0.621 ***	0.021
Mechanical harvesting vs. Mechanical plowing	ρ_{31}	0.524 ***	0.022
Mechanical spraying vs. Mechanical plowing	ρ_{41}	0.483 ***	0.030
Mechanical harvesting vs. Mechanical seeding	ρ_{32}	0.725 ***	0.017
Mechanical spraying vs. Mechanical seeding	ρ_{42}	0.448 ***	0.030
Mechanical spraying vs. Mechanical harvesting	ρ_{43}	0.337 ***	0.030
Likelihood ratio test	$\rho_{21} = \rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = \rho_{43} = 0$ (H_0); χ^2 (6) = 1772.26 ***		

Note: *** indicates significant at the 1% level.

The coefficients of independent variables in multivariate probit models are presented in Table 5. The Wald test indicates the model is significant (χ^2 (52) = 2090.25 ***). This justifies that the model fits well. Considering the possibility of multicollinearity, a collinearity diagnostic test was performed. The variance inflation factors of all explanatory variables are less than 3.13, suggesting that multicollinearity is not an issue [16]. Most of the explanatory variables we considered in this study show statistical significance and their signs are as expected.

Table 5. Results of multivariate probit models of adoption of four machinery technologies.

Variables	Mechanical Plowing		Mechanical Seeding		Mechanical Harvesting		Mechanical Spraying	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Maize sowing area	0.003	(0.005)	0.019 ***	(0.004)	0.021 ***	(0.004)	0.025 ***	(0.003)
Number of discrete fields in the farm	−0.003	(0.004)	−0.020 ***	(0.005)	−0.012 ***	(0.004)	−0.016 ***	(0.006)
Arable land area	0.016 ***	(0.004)	0.004	(0.003)	0.002	(0.002)	0.000	(0.002)
Crop diversity	0.031 **	(0.015)	0.002	(0.018)	0.078 ***	(0.015)	0.069 ***	(0.020)
Family labor	0.107 ***	(0.026)	0.084 ***	(0.028)	0.074 ***	(0.026)	0.000	(0.031)
Subsidy	0.478 ***	(0.050)	0.397 ***	(0.057)	0.546 ***	(0.052)	0.119 *	(0.066)
Technical assistance	0.245 ***	(0.072)	0.067	(0.076)	0.108	(0.069)	0.193 **	(0.079)
Economies of scale	0.001 *	(0.001)	0.002 ***	(0.001)	0.001 **	(0.001)	0.000	(0.001)
Northeast	0.775 ***	(0.080)	1.450 ***	(0.096)	0.589 ***	(0.081)	1.300 ***	(0.102)
North	1.141 ***	(0.081)	2.039 ***	(0.097)	1.186 ***	(0.081)	0.669 ***	(0.104)
Yellow-Huai River Valley	0.876 ***	(0.061)	1.760 ***	(0.080)	1.014 ***	(0.064)	0.539 ***	(0.088)
Northwest	0.907 ***	(0.102)	1.671 ***	(0.108)	0.722 ***	(0.097)	0.531 ***	(0.124)
South	0.038	(0.080)	0.138	(0.112)	0.325 ***	(0.082)	−0.073	(0.131)
Constant	−1.215 ***	(0.093)	−1.983 ***	(0.117)	−1.614 ***	(0.097)	−1.940 ***	(0.128)
Wald χ^2 (52)	2090.25 ***							
Log pseudo-likelihood	−7506.263							
Replications	200							
Number of observations	4165							

Note: * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. The Southwest is set as the base level in the regressions.

The maize sowing area has a positive effect on machinery technology adoption except for mechanical plowing. This result is consistent with Zhou et al. [11], Ma et al. [4], and Zhang et al. [10]. A greater maize sowing area promotes the adoption of agricultural machinery because machines are even more necessary to substitute for manual labor in this case. The number of discrete fields in the farm shows a negative impact on the adoption of mechanical seeding, mechanical harvesting, and mechanical spraying, because scattered fields increase the difficulty of machinery operation. Lai et al. [7] and Wang et al. [17] also found that land fragmentation decreases machinery use. The total areas of arable land on the farm indicate a positive effect on the adoption of mechanical plowing in maize production. Plowing is a labor intensive form of agricultural production. The larger the arable land on the farm, the more likely the farmer is to use machines for plowing.

Crop diversity exerts a positive impact on machinery technology adoption except for mechanical seeding. Higher crop diversity on their farms could motivate farmers to adopt more agricultural machinery technologies and use them on different crops to improve machinery use efficiency. Similarly, Mishra and Park [18] revealed that farm diversification could promote the adoption of more internet applications by U.S. farmers. More family participating in agricultural production labor increases the likelihood of machinery adoption in plowing, seeding, and harvesting. It could be that these farms are specializing in agricultural production. A number of machines are used on these farms to increase productivity and profitability. On the contrary, Zhou et al. [10] and Ma et al. [4] found that larger households would reduce the use of agricultural machinery because the farms have a sufficient labor supply. Subsidy increases the likelihood of using agricultural machinery. This result is in line with the findings from Ma et al. [4] Government subsidies lower the initial machinery purchase prices indirectly and boost agricultural mechanization [19].

Technical assistance contributes positively to the adoption of mechanical plowing and spraying. This result is parallel to the study of Carrere et al. [20] about the adoption of computers in citrus farming in Brazil. This is because technical assistance from agricultural professionals gives farmers a chance to learn the application of agricultural innovations, somehow promoting the adoption of new practices. Economies of scale affect machinery adoption positively. This finding is in accordance with the results for the adoption of computers by Brazilian citrus farmers [20]. Three reasons can explain this phenomenon. Firstly, China' s agriculture sector is predominantly small household farms whose typical size is estimated around 7.5 mu [21]. Small household farms are more willing to manage their agricultural activities with household labor and they have less incentive to invest in agricultural machinery than large farms. Secondly, due to the scale of production, the economic benefit that small household farmers could obtain from using agricultural machinery is less than their larger counterparts [22]. Thirdly, large economies of scale grant farmers the financial ability to invest in agricultural machinery.

Finally, machinery adoption also indicates regional differences in the six maize growing regions. Farmers located in the Northeast, North, Yellow-Huai River Valley, and Northwest are more likely to be machinery adopters than farmers in the Southwest. Farms in Southwest China have the lowest machinery adoption probability because of the hilly or mountainous terrain, which constrains large-scale machinery operation. Maize farmers in the Northeast and North may have higher machinery adoption odds than other regions because of the regions' plain topography and relatively large farm size. The regional differences in machinery adoption are due to uneven resource endowments such as topography, soil fertility, farm size, labor price, and off-farm employment among these regions.

4. Conclusions

In this study, household-level data on 4165 cases in six agroecological maize regions of China were used in multivariate probit models to identify the factors that influence maize farmers' decisions to adopt machinery technologies, with a specific focus on mechanical plowing, mechanical seeding, mechanical harvesting, and mechanical spraying. The findings support that the adoption of these four machinery technologies is interrelated and complementary. The results of multivariate probit models imply that maize sowing area, arable land area, crop diversity, family labor, subsidy, technical assistance, and economies of scale have positive effects on machinery adoption, while the number of discrete fields in the farm has a negative impact. Maize farmers in the Northeast and North have higher machinery adoption odds than other regions.

Based on these empirical results, the following recommendations are given to promote the adoption of agricultural machinery by Chinese maize farmers:

(I) Moderate scale production

Since maize sowing area, total areas of arable land in the farm, and economies of scale have positive effects on machinery adoption, moderately increasing the scale of agricultural production is a possible approach to reduce machinery operation costs and to facilitate machinery adoption. Especially in large-scale agricultural production, machinery is increasingly needed as a substitute for manual labor. We must be aware that scale production can increase the total agricultural output, but that the output per unit area is not always increased as the scale expands. Therefore, finding the moderate scale of production which facilitates machinery adoption and maximizes agricultural productivity is the key.

(II) Crop diversification

Crop diversity has a positive effect on machinery adoption. To an extent, an increase in crop varieties produced on the farm could promote the adoption of agricultural machinery and guarantee an overall income under price volatility in some agricultural products.

(III) Subsidizing agricultural machinery and its extension education

The adoption of machinery is influenced positively by subsidy. Obtaining subsidies from the government could boost the adoption of machinery by Chinese maize farmers, but it is only a temporary solution, and it also increases government administrative burdens. Farmers' intrinsic motivation is an important factor influencing agricultural machinery adoption. On the one hand, government can provide subsidies to support the purchase of agricultural machinery. In addition, agricultural machinery extension education is also necessary to make farmers realize the importance and benefits of agricultural mechanization.

(IV) Land consolidation

The number of discrete fields on the farm has a negative effect on machinery adoption. Land fragmentation is a barrier for machinery adoption because it increases the difficulty of mechanical operations. Considering the farm size growth, decreasing family labor, and land fragmentation in rural China, land consolidation might be an approach to promote machinery use. Merging scattered fields through land consolidation not only builds a convenient environment for large-scale agricultural mechanization but also improves agricultural productivity. However, small farms are more efficient in resource utilization than large farms. It is important to consolidate scattered fields into a size appropriate for machinery application but also optimal for resource utilization.

The proposals discussed above are just a general framework to promote the adoption of agricultural machinery by maize farmers in China. As indicated by the results in this study, the adoption of agricultural machinery shows regional differences. When it comes to a specific region, these proposals should be adjusted correspondingly to fit well with regional resource endowments.

There are also some shortcomings of this study. Due to data availability, this research could not add some explanatory variables regarding farmers' sociodemographic characteristics into the models. This study only considers whether farmers use machinery technologies or not, but the intensity of adoption of machinery technologies is not clear. Future work can focus on the intensity of adoption of machinery technologies in maize production. The economic and social impacts of using machinery in maize production compared with those who are not using it would be an interesting direction in the future as well.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available from Zhejiang University. After registration on the website http://ssec.zju.edu.cn/dataset/CRHPS/CRHPS.asp, accessed on 1 November 2021, you will get a personal account which allows full access to the database. However, the raw data cannot be downloaded. Only data analysis results and graphs are allowed for download with the permission of administers from Zhejiang University.

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