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Threshold effect or spatial spillover? The impact of agricultural mechanization on grain production

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ABSTRACT

The increase in agricultural machinery input contribution rate has been the most significant structural change in the input factors of grain production in recent years. In this study, we constructed a threshold regression model and a spatial Durbin model to investigate the threshold effects and the spatial spillovers of agricultural mechanization level on grain production, using panel data of 13 prefecture-level cities in Jiangsu, China, from 2000 to 2016. The results reveal that agricultural mechanization has a single threshold effect on grain yield, and that there is a significant spatial spillover effect of agricultural mechanization on grain yield. This means that the improvement of the mechanization level in one region, will significantly promote the increase in the grain yield in its surrounding regions, due to the cross-regional operation of agricultural machinerv.

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Agricultural mechanization: grain production; spatial spillover; threshold effect

1. Introduction

Grain production has always been an inevitable fundamental issue in agricultural development. Ensuring the sustainable and stable growth of grain yield is very important for the food security and social stability of developing countries. The history and experience of agricultural development worldwide show that the growth in grain yield is dependent upon the development and promotion of agricultural mechanization. Agricultural mechanization does not merely promote grain production efficiency, but also compensates for agricultural labor shortages, caused by the outflow of a large part of the agricultural population and alleviates the pressure of labor shortages in the process of grain production (Takeshima, Pratt, & Diao, 2013). China is one of the world's major agricultural countries, and Jiangsu Province is one of the largest grain production bases in China, with a grain yield that increased for 12 consecutive years from 2003 to 2015^{1} . Although Jiangsu's grain yield decreased slightly after 2015, its trend is high and

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¹Information source: Portal of the Central People's Government of the People's Republic of China (http://www.gov.cn/xinwen/2015-12/09/content_5021488.htm).

stable. Agricultural mechanization in Jiangsu Province has developed simultaneously with the grain yield. The agricultural mechanization level in Jiangsu Province reached 84% in 2018^2 .

However, agricultural mechanization is limited by the arable land area. The development of agricultural mechanization must be supported by the corresponding arable land area (Hayami & Kawagoe, 1989); otherwise, the positive impact of agricultural mechanization on grain production will be limited (Otsuka, 2013). The literature shows that, unlike other input factors, the action path of agricultural mechanization on grain production is not only realized through the improvement of the agricultural mechanization level in one region, but that the development of agricultural mechanization in other regions can also affect regional grain production through cross-regional operation (Ji, Yu, & Zhong, 2012). China faces the problem of mechanization development caused by the fragmentation of arable land, as in many developing countries, and it is difficult for machinery to play a role in promoting grain production when the arable land area is restricted. However, agricultural machinery can operate across regions due to its unique characteristics. In recent years, more than 90,000 combine harvesters have participated in crossregional operations in Jiangsu Province, and the annual income from cross-regional operations has stabilized at more than CNY 4 billion³.

Previous studies have shown that, for small farms in Asia, using machinery to perform a series of short-term tasks means an expensive investment in specialized machinery and that smallholders are reluctant to do so (Ruttan, 2000). Otsuka (2013) further points out that only investment in the mechanization of large farms, or at least in large machines, can provide a return to farmers. Thus, the average farm size in Asia would first have to be substantially increased from its current 1–3 ha to a more sizeable level, to achieve efficient mechanization.

The great development of agricultural mechanization in China contradicts the existing theories. For developing countries with serious contradictions between people and land resources, fragmented farmland is not suitable for large-scale machinery. However, the experience of Jiangsu Province shows that agricultural machinery can boost domestic grain production by enabling small-scale farmers to enjoy its services through cross-regional operations, without each farmer having to invest in it individually. Therefore, it is of great theoretical and practical significance for China and other developing countries, to estimate the threshold effects and spatial spillovers of agricultural mechanization level on grain production, based on the existing theories and the actual situation of China's mechanization development.

Previous studies mainly focused on the direct linear impact of agricultural mechanization level on grain production, based on macro data from developing countries and regions. Some studies have analyzed the substitution effect of agricultural machinery on labor (Dewan & Min, 1997) or regarded agricultural mechanization level as a part of the production function (Holst, Yu, & Grün, 2013), but they failed to consider the nonlinear relationship between agricultural

²Data source: Jiangsu People's Government website (http://www.jiangsu.gov.cn/art/2019/4/10/art_60085_8310758.html).

³Data source: The Central People's Government of the People's Republic of China (http://www.gov.cn/gzdt/2011-05/28/ content_1872521.htm).

mechanization level and grain production. Meanwhile, the spatial spillovers of agricultural mechanization level on grain production have rarely been considered in previous studies (Wang, Yamauchi, Otsuka, & Huang, 2016), resulting in a systematic overestimation of the effect of local agricultural mechanization on grain yield, and an underestimation of the total effect of agricultural mechanization level on grain yield (Zhang, Yang, & Reardon, 2015). There is a research gap, in that most studies lacked analysis of the spatial and nonlinear effects of agricultural mechanization level on grain production, and this study filled this gap by analyzing the threshold effects and the spatial spillovers of agricultural mechanization level on grain production.

We used the data of grain yield and agricultural production factor input in 13 prefecture-level cities in Jiangsu Province from 2000 to 2016, and used a threshold regression model and a spatial Durbin model (SDM) for empirical analysis, based on a literature analysis and empirical facts. We further implemented several robustness tests and several heterogeneity analysis based on the baseline results. Therefore, this study systematically examined the threshold effects and spatial spillovers of agricultural mechanization on grain production in Jiangsu Province.

The results show the economic effects of agricultural mechanization, such as increasing production and income. The study provides systematic interpretations, using the theoretical logic of cross-regional operations and the empirical testing of multi-period panel data. Thus, this study enriches the conclusions of existing studies and supplements the latest literature on the impact and mechanism of mechanized cross-regional operations in agricultural economics. In addition, the policy recommendations based on the research results in this study, are of great significance for the formulation and adjustment of agricultural mechanization development strategies, by relevant government departments and enterprises in developing countries or regions. They are also helpful in promoting the rational and efficient use of agricultural machinery in grain production. The policy recommendations also help promote the continuous improvement and coordinated development of agricultural mechanization between regions, and contribute to the intensification of grain production.

2. Literature review and conceptual framework

The production theory in microeconomics and agricultural economics shows that agricultural input factors such as labor, land, machinery, and fertilizer are still the main factors directly related to grain production, and they are also an important basis for ensuring the sustained growth of grain yield (Hayami & Ruttan, 1970). However, with the advancement of agricultural modernization and urbanization, the contribution rate of various factors to grain production is also undergoing structural changes, with the decrease in labor input contribution rate and the increase in agricultural machinery input contribution rate being the most significant (Qiao, 2017). Several studies have confirmed that agricultural labor transfer promotes the mechanical adoption behavior of farmers, due to the substitution relationship between labor and machinery in the agricultural production process. In other words, farmers can cope with a labor shortage by purchasing productive services or increasing their investment in machinery (Ji et al., 2012).

However, the impact of the level of agricultural mechanization on grain production will be adjusted by grain-sown areas. On the one hand, agricultural mechanization will promote grain production. Agricultural mechanization and the grainsown areas will form a complementary relationship in regions with large grainsown areas (Wang et al., 2016), which will improve the utilization rate and efficiency of mechanical operation, thus significantly increasing grain yield. On the other hand, the impact of the agricultural mechanization level on grain production may not be significant, or may even be negative. First, limited grain-sown areas are not conducive to the role of agricultural machinery, which makes it difficult for the machinery to exert its specialization effect (Ruttan, 2000). Second, in regions with small grain-sown areas, only small and medium agricultural machinery can be used to maximum effect, and it is difficult to use large and medium machinery. The restrictions on the variety of adopted machinery have reduced the impact of agricultural mechanization level on grain production (Pang, Dang, & Xu, 2021). Therefore, the impact of agricultural mechanization level on grain production may be nonlinear, and the magnitude and direction of the specific effect will be affected by the size of the grain-sown areas. The lack of scaled operations caused by the fragmentation of arable land is the main obstacle to the realization of agricultural mechanization in countries with large populations (Otsuka, 2013; Pingali, 2007).

The cross-regional operation of agricultural machinery can overcome the impediment of arable land fragmentation to the development of mechanization and cause agricultural mechanization to have a spatial effect. The cross-regional operation of agricultural machinery is a concrete manifestation of the geographical spillover effect of mechanization on agricultural production (Yang, Huang, Zhang, & Reardon, 2013). In new economic geography, spatial spillovers refer to the spatial impact caused by the change of a variable in a single spatial unit; that is, the impact of a variable change in one region on other regions (Anselin, 1988). If a region's agricultural mechanization is well developed, the advantages of



Figure 1. Conceptual framework of the impact of mechanization on grain yield. The figure shows the conceptual framework for the impact of agricultural mechanization on grain production. According to the theoretical analysis, the grain-sown area has a potential restriction on agricultural mechanization, which can be weakened by the cross-regional operation of agricultural machinery and reflected in the increase of grain production in this region and other regions. Source: Produced by the authors.

specialization and scale brought about by mechanization can be transferred to other regions through the cross-regional operation of agricultural machinery, and the input cost in the process of grain production can be reduced, so as to increase grain yield in other regions. As a result, thanks to the cross-regional operation of agricultural machinery, grain production in one region is not only affected by investment in local agricultural machinery but is also closely related to the level of agricultural mechanization in surrounding regions. If the agricultural mechanization level in one region is relatively high, then, through cross-regional agricultural services, the advantages of this kind of mechanical input can be transferred to surrounding regions. However, these advantages will gradually weaken as the geographical distance increases(as shown in Figure 1).

In summary, the impact of agricultural mechanization level on grain production has threshold effects and spatial spillovers, which have a strong policy-guiding significance for the government to promote the balanced development of agricultural mechanization and the sustainable growth of grain production, reasonably and efficiently. It is also helpful for optimizing the resource allocation of related agricultural machinery service enterprises, and for improving the level of operation and production management. However, there is no consistent conclusion on the existence, form of expression, and magnitude of the threshold effect and the spillover effect of agricultural mechanization level through the above theoretical analysis. Thus, it is essential to use quantitative analysis tools for further empirical research.

3. Empirical strategy and econometric model

To investigate the threshold effects of agricultural mechanization level on grain production in one region and the spatial spillovers in the surrounding regions systematically and comprehensively, the empirical strategy adopted in this study was as follows. (1) To disregard spatially dependent situations and nonlinear effects, we used the two-way panel fixed effect model (FEM) to estimate the impact of agricultural machinery input on the regional grain yield, based on the assumption that there is no threshold effect and spatial spillover, as a comparison of the baseline results. (2) We used a threshold regression model to study the nonlinear effects of agricultural mechanization on grain yield. (3) We measured the spatial autocorrelation of related variables by constructing the global Moran's index to provide a basis for further quantitative analysis. (4) Finally, the panel spatial econometric model, which took the spatial spillover effect into consideration, was used to study the impact of agricultural mechanization level on grain yield in one region and surrounding regions.

First, we assumed that there was no spatial spillover or threshold effect, and we constructed a two-way panel FEM based on the relevant research (Bi & Zhang, 2016). This model can help to solve the endogeneity problems of prefecture-city level panel data, which would lead to systematic bias in the estimation results, due to unobservable effects between different regions and between different years. The regression equation is as follows:

$$\ln Yie_{it} = \beta \ln Mac_{it} + \delta' X + \mu_i + \lambda_t + \varepsilon_{it}$$
(1)

In regression Equation (1), the explained variable $\ln Yie_{it}$ represents the natural logarithm of the total grain yield in prefecture-level city *i* in year *t*. The core explanatory variable $\ln Mac_{it}$ represents the natural logarithm of the total power of agricultural machinery invested in, by prefecture-level city *i* in year *t*, which reflects the agricultural mechanization level of prefecture-level city *i*. The estimated coefficient β measures the impact of prefecture-level city *i*'s agricultural mechanization level on grain production. The vector matrix *X* represents the set of control variables that may have an impact on regional grain production, including a series of agricultural production input variables and excluding other factors from interfering with the estimation of core explanatory variables. μ_i represents the prefecture fixed effect, and it controls the endogenous effects of the unobserved factors that only change with the region on the estimated results. λ_t represents the year fixed effect, which controls the endogenous effects of unobserved factors that vary only over time. ε_{it} represents the random error term in the regression equation.

Next, we took the threshold effect into consideration. The threshold effect refers to a structural mutation in the direction or magnitude of the effect of the independent variable on the dependent variable when a certain variable reaches a certain threshold. In this study, the grain-sown area will lead to a nonlinear impact of agricultural mechanization on grain production. Hence, we drew on the idea of threshold regression proposed by Hansen (1999), and selected the logarithm of the grain-sown area as the threshold variable, to establish the following single threshold regression model:

$$\ln Yie_{it} = \gamma_1 \ln Mac_{it} \cdot (\ln Are_{it} > \sigma_1) + \gamma_2 \ln Mac_{it} \cdot (\ln Are_{it} \le \sigma_1) + \delta' X + \mu_i + \lambda_t + \varepsilon_{it}$$
(2)

In Equation (2), y_1 and y_2 are the parameters to be estimated, indicating the differential impact of agricultural mechanization on grain production at different intervals; σ_1 is the threshold value and the optimal threshold value is generally determined by the grid research method; I (·) is an indicative function, which equals 1 when the conditions in parentheses are met, and 0 otherwise. The meanings of the other variables are the same as those in Equation (1).

Finally, this study used a quantitative method to investigate whether there is a spatial autocorrelation between grain production and agricultural mechanization in each region. Presently, the most commonly used method to measure spatial correlation is Moran's index (Moran's I) (Moran, Kierzek, & Turner, 1993), which was proposed by Moran in 1950. In a mathematical sense, this index explains the first law of geography: everything is correlated with everything else, and things that are close to each other are more correlated than things that are far away (Tobler, 1970). This study selected the global Moran's index for the measurement of spatial autocorrelation, and its calculation formula is as follows:

Moran's I =
$$\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y}) / S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$$
 (3)

In Equation (3), $S^2 = \sum_{i=1}^{n} (Y_i - Y_i)^2 / n$ is the sample variance, and $\overline{Y} = \sum_{i=1}^{n} Y_i / n$ is the sample mean. Y_i is the actual value of grain yield or the total power of agricultural machinery in prefecture-level city *i*, and *n* is the total number of prefecture-level cities. *W* is the spatial weight matrix, the element w_{ij} in the spatial weight matrix *W* represents

the reciprocal of the economic distance between two prefectural-level cities i and j_i^4 describes the spatial weight value determined by each pair of prefecture-level cities, and embodies the essential characteristics of the correlation and mutual influence between geographical regions in spatial econometrics. W is a symmetric matrix, we have $w_{ii} = w_{ii}$, and the main diagonal element $w_{11} = w_{22} = w_{33} = \ldots = w_{nn} = 0$. Through the measurement of spatial autocorrelation, this study used a spatial econometrics method to demonstrate the impact of agricultural mechanization level on grain production and separated the direct impacts from the spatial spillovers. Spatial econometric models of panel data mainly include the spatial autoregressive (SAR) model and the spatially lagged model (SLM). The SAR model contains spatial lag variables, considering the dependence of the explained variables in a certain region on the explained variables in neighboring regions, while the SLM assumes that the explained variables in a certain region depend on the independent variables of their neighbors (Drukker, Prucha, & Raciborski, 2013; Elhorst, 2010). A new spatial panel econometrics method, the SDM, which is a combination of the SAR and the SLM, was introduced in this study. In the SDM, the explained variables of one region will be affected by both the explanatory variables and the explained variables of its surrounding regions at the same time. The SDM has the following advantages over the traditional spatial econometric model. (1) The SDM ignores the specific generation mechanism and the expression form of spatial variables to ensure that the coefficients under the model are all unbiased (Elhorst, 2012). (2) This model includes the correlation between the spatial lag term of explanatory variables and the explained variables (LeSage, Fischer, & Scherngell, 2007). (3) It does not limit the scope of the spatial spillovers in advance (Elhorst, 2012). The panel SDM equation is as follows.

$$\ln Yie_{it} = \alpha W \ln Yie_{jt} + \beta_1 \ln Mac_{it} + \delta_1' X + \beta_2 W \ln Mac_{jt} + \delta_2' W X + \mu_i + \lambda_t + \varepsilon_{it}$$
(4)

In the SDM Equation (4), the explained variables $\ln Yie_{it}$ and the explanatory variables $\ln Mac_{it}$ represent the natural logarithms of total grain yield and the total power of agricultural machinery in prefecture-level city *i* in year *t*, respectively. $W\ln Yie_{it}$ and $W\ln Mac_{jt}$ represent the spatial lag variables of the explained and explanatory variables, respectively, including the spatial weight between prefecture-level city *i* and other prefecture-level cities *j* in year *t*. Other related variables have the same meaning as in regression Equation (1).

4. Data

Jiangsu Province is an important grain production base in China. The proportion of the grain-sown area in Jiangsu Province has always been above 62% and ranks first in China. The total power of agricultural machinery in Jiangsu Province shows a continuous growth trend, mirroring the increase in grain yield. As the first major

⁴The economic distance between two regions is generally expressed by the cost of commuting. This study considered the data accuracy and availability requirements and, based on the relevant literature, used the time provided by Google Maps to drive motor vehicles between the two regions in our calculations. This also replicates the actual situation of driving agricultural machinery for cross-regional operations.

Variables	Symbol	Unit	Mean	Std.dev.	Min	Max
Grain yield	Yie	ton	2 610 092.00	1 507 608.00	591 627.00	7 080 599.00
Agricultural machinery	Мас	kw	2 863 062.00	1 530 822.00	992 200.00	7 123 300.00
Grain acreage	Are	hectare	401 950.30	231 251.90	94 060.00	981 570.00
Plant industry labor	Lab	person	631 476.90	428 900.60	118 600.00	2 071 400.00
Chemical fertilizers	Fer	ton	257 207.00	180 274.90	51 835.00	703 405.00
Pesticide use	Che	ton	6 831.47	3 675.87	1 660.00	15 967.00
Plastic use	Plas	ton	6 913.97	5 900.33	1 265.00	30 314.00
Agricultural diesel use	Die	ton	69 188.99	52 985.74	15 230.00	265 033.00
Rural electricity use	Elec	10 mw	902 434.00	1 250 145.00	19 691.00	6 097 800.00

Table 1. Descriptive statistics of the variables.

grain-producing province to carry out agricultural mechanization in China, Jiangsu Province has developed a batch of agricultural machinery cross-regional operation teams in its northern region, which enables it to export specialized agricultural machinery services to the surrounding areas. Therefore, it is of great importance to study the threshold effects and spatial spillovers of the agricultural mechanization level on grain production in Jiangsu Province to achieve the goal of agricultural modernization and stabilize grain yield in China and other developing countries.

The data in this study were derived from the *Jiangsu Rural Statistical Yearbook* (2001–2017), which provides prefecture-level city statistics on crop yield, the total power of agricultural machinery, crop sown area, rural labor force, agricultural energy, and material consumption, and covers relatively comprehensive data on grain output and input. In combination with the related literature, according to the requirements of the research and empirical models on the data, this study finally selected the data of 13 prefecture-level cities in Jiangsu Province from 2000 to 2016. The variable description and descriptive statistical report of the data needed for our empirical study are shown in Table 1.

From the variation trend of the explained variables (as shown in Figure 2), the grain yield of Jiangsu Province from 2000 to 2016 was relatively stable, and the production capacity remained at a high level. The lowest amount of grain yield in the 17-year period was 2,471.85 billion kg, in 2003, and the highest was 3,561.34 billion kg, in 2015. Since 2003, the grain yield has maintained a steady growth. This shows that although there was a trend of continuous labor force outflow in the agricultural production sector, it did not have a substantial negative effect on the changes in grain yield in Jiangsu Province. At the same time, as the core explanatory variable, the total power of agricultural machinery has shown an upward trend (as shown in Figure 2), which may form a substitution relationship with the rural labor force. Although the land system has not changed significantly, the total power of agricultural machinery in Jiangsu Province still shows a trend of continuous development. In 2015, the total power of agricultural machinery reached 48.25 million kW, which is about 5.64 times that of 1978. The agricultural mechanization level in the province exceeded 80% by 2016, and the mechanical sowing and harvesting rates of corn rose steadily, reaching 90% and 81%, respectively. The total area of mechanical rice planting reached 1.66 million ha, the machine insertion rate exceeded 75%, and the mechanization level continued to increase. The returning rate of rice and wheat straw reached 53%, and the

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Figure 2. Grain yield and total power of agricultural machinery in Jiangsu province from 2000 to 2016. The figure describes the common growth trend between Jiangsu's grain yield and the total power of agricultural machinery. Source: Jiangsu Rural Statistical Yearbook from 2001to 2017.

returning area was over 2.72 million ha.⁵ In addition, the cross-regional operation of agricultural machinery in Jiangsu Province continued to grow, and the crossregional income of agricultural machinery in 2016 was stable at about CNY 700 million,⁶ which was the highest it had ever been.



Figure 3. Spatial distribution of grain yield, total power of agricultural machinery and grain sown area of Jiangsu province's prefecture-level cities from 2000 to 2016. The figure is mapped with ArcGIS using the 2000–2016 sample mean data, and the graduated colors describe the grain yield and grain-sown area: darker colors mean there is more grain yield and grain-sown area. The size of circle describes the total power of agricultural machinery: larger size means there is more total power of agricultural machinery. The grain yield, the total power of agricultural machinery and the grain-sown area all have a certain spatial correlation. Source: Jiangsu Rural Statistical Yearbook from 2001to 2017.

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⁵Data source: China Jiangsu Net (http://www.jsnews.jschina.com.cn/jsyw/201703/t20170317_228148.shtml).

⁶Data source: Jiangsu Provincial Committee News Network (http://www.zgjssw.gov.cn/m/shixianchuanzhen/lianyun gang/201604/t2782412.shtml).

Figure 3 shows the geographical distribution of the total grain yield, the total power of agricultural machinery, and grain-sown area in 13 prefecture-level cities in Jiangsu Province from 2000 to 2016. In the figure, the grain yield and grainsown area of all prefecture-level cities are distinguished by color, and the color range - from light to dark - represents the grain yield and grain sown area, ranging from low to high. The total power of agricultural machinery is represented by an area with a circular shape. A larger circle indicates a higher total machinery power. On the one hand, by observing the spatial distribution of the total power of agricultural machinery and grain-sown area, it can be concluded that the greater the sown area of a prefecture-level city, the greater the corresponding total power of agricultural machinery. This shows that the development of the total power of agricultural machinery will be affected by the grain-sown area. On the other hand, by observing the spatial distribution law of the total grain yield and the total power of agricultural machinery in each prefecture-level city, it was found that regions with large grain yield or large total power of agricultural machinery also show similar characteristics in the surrounding prefectural-level cities. There may be a spatial correlation between the two variables, which we call spatial autocorrelation. In addition, for prefecture-level cities with large grain yields, the circular pattern representing the total power of agricultural machinery is correspondingly larger, which indicates that there is also a certain statistical correlation between the two variables. Finally, by comparing the total power of agricultural machinery in a prefecture-level city with the grain yields in its surrounding prefecture-level cities, it is not difficult to find that if the agricultural mechanization level of a prefecturelevel city is higher, then the grain yields of the surrounding prefecture-level cities are also higher. Therefore, it can be found directly from the figure that the improvement of the agricultural mechanization level in a certain place, may positively affect the grain yield of local cities, as well as have a certain positive impact on grain production in neighboring cities, through the geographical cross-regional operation of agricultural machinery. This means that agricultural mechanization has a spatial spillover effect on grain production.

5. Empirical analysis

5.1. Two-way panel FEM estimation

Based on the empirical strategy and econometric model discussed in Section 3, this study first investigated the direct effect of local agricultural mechanization on grain production through the two-way panel FEM, without considering the nonlinear relationship and the spatial correlation of variables. Table 2 reports the estimated results of the six models based on regression Equation (1); Models 1–3 have neither prefecture fixed effects nor year fixed effects, compared to Models 4–6. There are differential numbers of control variables in the six models. Models 1 and 4 have no control variables, while Models 3 and 6 have all control variables. From the significance level of the estimated coefficient of the core explanatory variable ln*Mac* in each model, it can be seen that the core estimator of the model remained robust, regardless of whether the fixed effects were controlled or whether the

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		POLS			FEM	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables	(1)	(2)	(3)	(4)	(5)	(6)
In <i>Mac</i>	0.600***	0.229***	0.128***	0.544***	0.059*	0.054**
	(0.057)	(0.031)	(0.034)	(0.058)	(0.035)	(0.026)
In <i>Are</i>		0.998***	1.024***		0.97***	1.032***
		(0.068)	(0.078)		(0.052)	(0.055)
In <i>Fer</i>		0.146**	-0.021		0.102	0.048
		(0.070)	(0.078)		(0.064)	(0.052)
In <i>Lar</i>			-0.056***			-0.032
			(0.018)			(0.027)
In <i>Pes</i>			-0.006			0.039
			(0.040)			(0.037)
In <i>Pla</i>			0.005			0.013
			(0.018)			(0.120)
In <i>Die</i>			-0.018			0.026
			(0.045)			(0.024)
In <i>Ele</i>			0.030**			0.023
			(0.012)			(0.021)
Prefecture FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
R	0.595	0.872	0.891	0.796	0.953	0.956

Table 2. The estimation results of the two-way panel fixed effects model (FEM).

The White heteroskedasticity-robust standard errors are in parentheses. ***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively. All regressions have 221 observations.

number of control variables was increased or decreased. The estimated results of Model 1 show that when only the total power of agricultural machinery is included in the model as an explanatory variable, each 1% increase in the agricultural mechanization level will result in an increase of approximately 60% in grain yield. With the increasing number of control variables and the control of twoway fixed effects, the interference caused by other input factors and unobservable factors on the regression of core explanatory variables was stripped out, and the average partial effect of the agricultural mechanization level on local grain production gradually decreased. Finally, Model 6 reports the results of the model estimates, controlling for all other factor inputs and two-way fixed effects, showing that a 1% increase in the agricultural mechanization level will boost grain yield by more than 5%. The nonlinear relationship between variables cannot be observed if we use the linear model directly. By comparing the estimated results of Models 1-6, it can be concluded that the estimation results of pooled ordinary least squares (POLS) without controlling for the fixed effects may cause a systematic overestimation of the coefficient of the core explanatory variables. Furthermore, the panel FEM will systematically underestimate the positive total effect of agricultural mechanization on regional agricultural production due to ignoring the spatial spillover, considering that there is a spatial autocorrelation between cities in Jiangsu Province which was brought about by the cross-regional operation of agricultural machinery. In addition, FEM and POLS only consider the linear effects, while ignoring the nonlinear effects of agricultural mechanization on grain yield.

Table 3. The estimation resu	ults of the threshold re	gression model (TRM).				
		POLS-TRM			FE-TRM	
	Model 7 (1)	Model 8 (2)	Model 9 (3)	Model 10 (4)	Model 11 (5)	Model 12 (6)
Panel A: Threshold value Threshold estimate 95% confidence interval	12.579 [12.297.12.666]	13.001 [12.992.13.008]	13.037 [11.452.13.796]	12.064 [12.049.12.067]	12.579 [12.363.12.655]	12.579 [12.224.12.655]
Panel B: The effect of mechan	ization level on grain yie	pla				
InMac(InAre<\sigma_1)	0.549*** (0.077)	0.1/0**** (0.030)	0.176*** (0.033)	0.535*** (0.032)	-0.140*** (0.051)	-0.076 (0.054)
InMac(InAre≥σ₁)	0.579*** (0.039)	0.255*** (0.031)	0.160*** (0.048)	0.546*** (0.031)	0.218*** (0.023)	0.116*** (0.036)
Panel C: The effect of control	variables on grain yield					
InAre		1.182***	1.092***		1.234***	1.216***
InFer		(10.00) -0.198***	-0.016		(0.049) -0.103***	(0c0.0) -0.016
		(0.033)	(0.061)		(0.021)	(0.052)
In <i>Lar</i>			-0.08/*			/0.02/
InPes			0.093			-0.009
;			(0.047)			(0.033)
InPla			0.008 (0.044)			0.046** (0.021)
InDie			0.073**			0.035
			(0.024)			(0.028)
Inere			-0.012			0.010 (0.013)
Prefecture FE	No	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
R ²	0.625	0.916	0.952	0.619	0.895	0.900
Panel A reports the estimated th heteroskedasticity-robust stanc observations.	reshold value, and Panel B lard errors are in parenthe	reports the effect of mecheses. ***, ** and * mean	nanization level on grain y significant effects of the v	eld. Panel C reports the eff ariables at 1%, 5% and 10	ect of control variables on g 3% levels, respectively. All r	rain yield. The White egressions have 221

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Hypothesis test	F value {P-value}	Threshold value	95% confidence interval
H0: no threshold; H1: 1 threshold	9.270*	12.579	[12.224,12.655]
	{0.084}		
H0: 1 threshold; H1: 2 thresholds	0.940	11.994	[11.992,11.998]
	{0.810}		

 Table 4. The results of threshold effect test and threshold evaluation of total power of agricultural machinery on grain production.

P-values are estimated using Bootstrap method of 500 times' samplings. P-values for joint significance tests are in curly braces and 95% confidence interval are in brackets. ***, ** and * mean the significance level of F-statistic at 1%, 5% and 10% levels, respectively.

5.2. Threshold effect estimation

Table 3 reports the results of the threshold regression estimation. The first four columns report the POLS threshold estimation results, while the remaining columns report the FE threshold estimation results, controlling for the prefecture fixed effect. Agricultural mechanization may have an endogeneity problem, because it can be affected by soil quality and other non-observable factors that will affect grain production. The POLS threshold regression estimation is unable to eliminate the inherent unobservable effects, resulting in biased results. The results of Panel A reveal that the impact of agricultural mechanization level on grain production has a grain-sown area threshold effect. We found that the threshold value increased and stabilized at 12.579, with a 95% confidence interval of [12.244,12.655], by gradually increasing the control variables. Therefore, we chose Model 12 as having the best control variables and as the final threshold regression result. According to the test results of the threshold effect of Model 12 (as shown in Table 4), the F value of the single threshold model rejects the null hypothesis at the significance level of 10%. However, the double threshold model fails to reject the null hypothesis, so it can be considered that agricultural mechanization level has a single threshold effect on grain production.⁷ The results show that when the logarithm of the grain-sown area was less than 12.579, the estimated coefficient of agricultural mechanization level on grain yield was -7.6%, but this was not statistically significant. It indicates that the marginal utility of agricultural mechanization to grain yield is weakened when the grain-sown area is small. When the logarithm of grain sown area is greater than or equal to 12.579, the estimated coefficient of agricultural mechanization level to grain production is 11.6%, and it passes the 1% significance level test. This indicates that when the grain-sown area crosses the threshold, the promotion effect of agricultural mechanization level on grain yield is significantly improved. Specifically, the prefecture-level cities to the left-side of the grain-sown area threshold, primarily had a lower proportion of grain production, and their grain-sown area and the market capacity of agricultural machinery was relatively small. As a result, it is difficult for their local agricultural mechanization to play a role in increasing local grain production. On the contrary, in the prefecture-level cities with large grain-sown areas, the effect of local agricultural mechanization on increasing grain production is more obvious. The results of

⁷.Model 7 to Model 12 all passed the single-threshold test. Due to space limitations, only the test results of Model 12 are reported, and the remaining results are available on request.

Model 10 show that the estimated coefficients of agricultural mechanization levels are independent of the threshold, which may be due to the fact that key input factors affecting grain production were not included in the control variables, resulting in errors in the estimates. The FE threshold model, which only controls for the total power of agricultural machinery, shows that the impact of agricultural mechanization on grain yield is significantly positive, regardless of whether the threshold value is crossed. However, by further controlling for the factors that affect grain yield, we were able to identify the nonlinear relationship between mechanization and grain yield. After Model 11 further controlled for the major influencing factors of grain yield, the estimated results were similar to those in Model 12. Due to the restriction of grain-sown area, the promotion effect of agricultural mechanization level on grain production may be limited. However, the cross-regional operation of agricultural machinery in China makes it possible for the specialization and scale effects of agricultural mechanization to spread to other regions and thus weaken the restrictive effect of grain-sown area, so that the regions with small grain-sown areas can enjoy the yield-increasing effect of mechanization development.

5.3. Spatial autocorrelation measurement based on the global Moran's index

In this study, the global Moran's index of grain yield and the total power of agricultural machinery in Jiangsu Province from 2000 to 2016 was calculated according to Equation (3) (as shown in Figure 4). It can be seen from Figure 4 that the global Moran's index of the above two variables is positive and far from 0. Although the value of Moran's index fluctuates to a certain extent in different years, it shows an overall annual increasing trend. All the Moran's index values were significant at the 5% level. The above results show that the grain production and agricultural mechanization level of all prefecture-level cities have significant spatial autocorrelations; they show a certain spatial agglomeration phenomenon, and the effect becomes more prominent over time.

Moran's index indicates the spatial correlation between grain yield and the total power of agricultural machinery. However, it is still impossible to determine the impact of the total power of agricultural machinery on grain production. This study further used a spatial econometrics method to empirically study the spatial spillover of the agricultural mechanization level on grain production.

5.4. SDM estimation considering spatial autocorrelation

According to the above core variable's global Moran's index measurement results, we first used the SDM method to empirically analyze the spatial autocorrelation. The estimated results of each model, using the SDM regression equation provided by Equation (4), are reported in Table 5. It should be pointed out that because the SDM method is not a linear regression, the estimated coefficients obtained cannot directly reflect the magnitude of the spatial spillover, and they have to be

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Figure 4. The global Moran's index of grain yield and the total power of agricultural machinery of Jiangsu province's prefecture-level cities from 2000 to 2016. The figure shows the Global Moran's Index of grain yield and total power of agricultural machinery in Jiangsu Province. There is a positive spatial correlation in grain yield and total power of agricultural machinery respectively given that the Global Moran's Index is greater than 0. Source: Calculated by the authors.

decomposed further by partial differentiation. Table 6 displays the direct effects, spatial spillovers, and total effects obtained from the decomposition of the estimated coefficients in each model.

Model 13 to Model 16 in Table 5 provide the estimated results of random-effect SDM as a control group, and Model 17 to Model 20 report the estimated results of the FE SDM. The results of the FE SDM, which controls for the unobservable effects in different regions and years, are more accurate. The estimated results of Model 17, reported in Column 5 in Table 5, controls only for the total power of agricultural machinery and its spatial lag term. Model 18 to Model 20 report the estimated results after gradually increasing the number of control variables. Model 20 contains all the control variables and fixed effects. Therefore, this study used the regression coefficient of Model 20 as the baseline result. This shows that when other conditions remain unchanged, an increase in the level of agricultural mechanization will significantly promote local grain production. For every 1% increase in the total power of agricultural machinery, the local grain yield increases by 7.5%. The increase in agricultural mechanization level will also have a spillover effect on grain production in the surrounding prefecture-level cities. Every 1% increase in the total power of local agricultural machinery will significantly increase the grain yield of the surrounding prefecture-level cities by 86.6%. The total effect of increasing grain yield is approximately 94.1%. This shows that the socialized agricultural service market, represented by the cross-regional operation of agricultural machinery, is not limited to a single region, and its specialization effect can be expanded by taking advantage of the differences in the maturity period of grain crops at different times, so as to significantly improve grain yields in other regions. This regression result means that the developmental advantages of the

	RE-SDM				FE-SDM			
	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In <i>Mac</i>	0.476***	0.035	0.034	0.010	0.489***	0.051	0.050	0.020
	(0.082)	(0.035)	(0.034)	(0.022)	(0.079)	(0.036)	(0.035)	(0.022)
In <i>Are</i>		0.946***	0.951***	0.997***		0.905***	0.912***	0.953***
		(0.048)	(0.048)	(0.042)		(0.047)	(0.048)	(0.050)
In <i>Fer</i>		0.098	0.101*	0.043		0.087	0.090	0.020
		(0.060)	(0.060)	(0.051)		(0.066)	(0.065)	(0.053)
In <i>Lab</i>			-0.012	-0.049**			-0.016	-0.049*
			(0.019)	(0.023)			(0.024)	(0.026)
In <i>Pes</i>				0.046				0.056
				(0.036)				(0.038)
In <i>Pla</i>				0.005				-0.009
				(0.017)				(0.019)
In <i>Die</i>				0.051**				0.031
				(0.024)				(0.022)
In <i>Ele</i>				0.041**				0.042**
				(0.019)				(0.018)
W× In <i>Yie</i>	0.721***	0.743***	0.743***	0.706***	0.715**	0.741***	0.740***	0.722***
	(0.046)	(0.032)	(0.032)	0.044	(0.046)	(0.033)	(0.032)	(0.041)
W× In <i>Mac</i>	-0.238	0.099	0.106	0.113	-0.249	0.077	0.091	0.242**
	(0.164)	(0.079)	(0.083)	(0.093)	(0.158)	(0.064)	(0.072)	(0.089)
W× InAre		-0.588***	-0.595***	-0.509***		-0.562***	-0.568***	-0.496***
		(0.082)	(0.083)	(0.139)		(0.081)	(0.083)	(0.125)
W× InFer		-0.054	-0.053	0.041		-0.059	-0.0/0	-0.125
		(0.070)	(0.112)	(0.155)		(0.072)	(0.106)	(0.169)
W× InLab			0.013	0.224**			0.024	0.249**
We also De a			(0.039)	(0.105)			(0.043)	(0.094)
W× InPes				-0.083				-0.033
W4 . I. 0/ -				(0.057)				(0.057)
W× InPla				0.003				-0.003
W4 . I. D'.				(0.071)				(0.060)
w× indie				-0.062				-0.191
Why In Ela				(0.109)				(0.111)
w× meie				0.048				0.039
Drofocturo FE	No	No	No	(U.USZ)	Voc	Vac	Vac	(0.047) Voc
	No	No	No	No	Voc	Voc	Voc	Voc
rear FE	INU 0.724	0.070		0.001	165	105	0.014	105
n	0./34	0.979	0.980	0.981	0.289	0.914	0.914	0.919

 Table 5. The estimation results of the spatial Durbin model (SDM) considering the Spatial spillover.

The White heteroskedasticity-robust standard errors are in parentheses. ***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively. All regressions have 221 observations.

Tab	ole 6	 Direct 	effect,	Spatial	spillover,	and	total	effect.
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	Direct effect		Spatial spillover		Total effect	
Variables	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
In <i>Mac</i>	0.075***	0.029	0.866***	0.291	0.941***	0.306
In <i>Are</i>	0.994***	0.056	0.647	0.425	1.640***	0.453
In <i>Fer</i>	0.002	0.069	-0.37	0.59	-0.368	0.637
In <i>Lab</i>	-0.006	0.039	0.705**	0.334	0.699*	0.361
In <i>Pes</i>	0.055	0.041	0.032	0.19	0.087	0.208
In <i>Pla</i>	-0.009	0.035	-0.026	0.236	-0.035	0.267
In <i>Die</i>	-0.004	0.036	-0.558	0.372	-0.561	0.397
In <i>Ele</i>	0.056**	0.029	0.223	0.179	0.279	0.196

****, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively.

improvement of the agricultural mechanization level in one prefecture-level city can be transferred to its surrounding cities by means of the cross-regional operation of agricultural machinery. The estimated coefficients of the core explanatory variables in Model 17 to Model 19, are basically similar to the baseline regression results, which not only shows that the model used in this study is reasonable and the estimated results are relatively robust, but also confirms that there is a spatial spillover effect of agricultural mechanization on grain production.

In addition, by comparing the SDM estimation results with the POLS estimation results obtained above, it is not difficult to find that a linear estimation, without considering the spatial autocorrelation between different regions, would lead to a systemic overestimation of the direct effect of agricultural mechanization on local grain production growth. The total effect of agricultural mechanization would have been underestimated, because its spatial spillover was neglected. Comparing the SDM estimation results with the FEM regression results, it was found that the FEM directly eliminated the spatial spillover that may exist in variables, which not only ignored the spatial interaction between geographically adjacent regions, but also caused the total effect of agricultural mechanization on local grain yield increase to be systematically underestimated.

5.5. Robustness checks

This study further reported the likelihood ratio (LR) trend of a single-threshold test, which is reported in Figure A1 in the Appendix, to ensure the robustness of the threshold regression results. The results show that the single-threshold statistical effect is better in terms of the grain-sown area. To ensure the robustness of the threshold estimation results, this study performed grouped regression of the samples according to whether the grain-sown area is greater than 12.579. The grouped regression results in Table A1 columns 1 and 2 are similar to the baseline regression results. When the grain-sown area is less than the threshold value, the mechanization has no positive impact on the grain yield. The impact of mechanization on grain yield is significantly positive when the grain-sown area is greater than the threshold value. It can be seen that the threshold effect results are relatively stable. At the same time, because the threshold regression model can independently select the threshold value and the number of thresholds, and has a strong explanatory nature, the baseline regression results are more effective.

We also carried out the following robustness checks to ensure that the above SDM regression results remain stable in different situations. (1) We measured the spatial spillover using SLM instead of SDM. (2) We ran the baseline regression using SDM, while we used common standard errors instead of White heteroskedasticity-robust standard errors. (4) We ran the baseline regression using SDM, while we used a first-order contiguity weight matrix, which is a 0–1 matrix where w_{ij} equals 1 if regions *i* and *j* have geographical contiguity and 0 otherwise, as the spatial weight matrix. The results of the robustness checks are reported in Tables A1 and A2 in the Appendix.

This study further estimated the direct, spillover, and total effects on the basis of the robustness checks. Except for the fact that the SLM could not be decomposed due to the structure of the regression equation, the estimation and decomposition results of the other three models were basically consistent with the baseline estimation results in terms of the direction, magnitude, and significance of the regression coefficients, indicating that the baseline estimation results remain robust. However, SDM is more comprehensive and accurate than SLM and SAR in expressing the relationship between agricultural mechanization level and grain yield. Due to the difference in unobservable factors, there are more or less heteroscedasticity or autocorrelation problems between different prefecture-level cities and years, which had to be controlled for in the regression. Also, the geographic contiguity weight matrix could more accurately describe the spatial correlation between different prefecture-level cities, compared to the first-order contiguity weight matrix, so that the estimation results were more accurate. In summary, the baseline results were not only robust, but also the most consistent and effective.

5.6. Heterogeneity analysis of different grain varieties

This study further used sub-samples to investigate whether there was a difference in the impact of the increase in agricultural mechanization level on different grain varieties, considering the differences in the use of agricultural machinery and grain yield, which result from the differences in the planting structure, geographic spatial distribution, and planting environment of different grain varieties. The changes in the yield of rice, wheat, corn, and soybean were used as the research objects, considering the universality and representativeness of the grain crops planted in Jiangsu Province.

Table 7 reports the heterogeneity analysis results of the threshold model and the SDM, and Table 8 reports the decomposition results of the SDM. The control variables of the threshold model were consistent with Model 12, while the control variables and decomposition methods of the SDM were all consistent with Model 20. The threshold estimation results of the first four columns in Table 7 suggest that agricultural mechanization level has an obvious grain-sown area threshold effect on corn and wheat production. If the grain-sown area of corn is less than the threshold value, the impact of agricultural mechanization on corn production is negative. When the grain-sown area of corn is more than the threshold value, the effect of agricultural mechanization on corn production is significantly positive. When the agricultural mechanization level is less than the threshold value, the impact of agricultural mechanization on wheat production is negative. When it is larger than the threshold value, its influence is not significant. However, there is no obvious threshold effect for rice and soybean, and the constraints of grain-sown area for these two varieties on the effect of agricultural mechanization are not significant. What is more, it can be seen from Table 8 that the direct effects and spatial spillovers of agricultural mechanization level on different types of grain production are significantly different. The improvement of the agricultural mechanization level directly promoted only local rice production but had no significant effect on local wheat, corn, and soybean production, which may be related to the

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	<u> </u>	, TF	RM			SE	DM	
Variables	Rice (1)	Wheat (2)	Corn (3)	Soybean (4)	Rice (5)	Wheat (6)	Corn (7)	Soybean (8)
$\ln Mac(\ln Are < \lambda_1)$	0.071**	-0.355***	-0.325*	0.030				
In <i>Mac</i> (In <i>Are</i> ≥λ₁)	(0.032) 0.076** (0.032)	(0.081) 0.025 (0.056)	(0.181) 0.306*** (-0.084)	(0.081) 0.038 (0.082)				
In <i>Mac</i>	. ,	. ,	. ,	. ,	-0.007	-0.180***	0.043	-0.227
In <i>Are</i>	1.004***	1.287***	0.910***	1.019***	(0.049) 1.009*** (0.032)	(0.057) 1.079*** (0.052)	(0.219) 1.016** (0.470)	(0.165) 0.798*** (0.062)
In <i>Fer</i>	0.050 (0.056)	-0.209*** (0.078)	0.094 (0.158)	0.029 (0.150)	0.047 (0.073)	-0.230** (0.099)	0.033 (0.175)	-0.458 (0.309)
ln <i>Lab</i>	-0.015	-0.155***	0.079	-0.002	0.016	0.243***	0.158	0.153**
InPes	(0.024) -0.120*** (0.027)	(0.034) 0.222*** (0.052)	(0.062) -0.262** (0.102)	(0.062) -0.158 (0.005)	(0.028) -0.089 (0.056)	(0.050) 0.079 (0.086)	(0.176) -0.481*** (0.148)	(0.063) 0.185 (0.106)
In <i>Pla</i>	(0.037) 0.083*** (0.023)	(0.032) 0.041 (0.033)	0.098	(0.093) 0.089 (0.059)	0.023	0.106****	0.389***	(0.190) 0.166*** (0.064)
In <i>Die</i>	0.052 (0.033)	0.019 (0.044)	0.126 (0.084)	0.249*** (0.084)	0.046 (0.033)	0.039 (0.083)	-0.358* (0.204)	0.361* (0.202)
In <i>Ele</i>	-0.001	0.091***	-0.082**	-0.056	0.035	-0.098	-0.023	-0.269***
W× InYie	(0.015)	(0.021)	(0.039)	(0.039)	(0.029) 0.077	(0.043) 0.155	(0.134) 0.745**	(0.091) -0.531**
					(0.231)	(0.102)	(0.317)	(0.235)
W× In <i>Mac</i>					0.621**	0.042	9.702***	2.147**
₩× InAre					(0.256) 0.133	(0.490) 0.864***	(1.481) -6.994***	(0.915) -1.375***
					(0.312)	(0.332)	(1.872)	(0.493)
W× InFer					0.138	-0.392	2.902**	-1.227
Wx In <i>Lab</i>					(0.476)	(0.689) 1.432**	(1.222)	(1.463)
					(0.336)	(0.584)	(1.606)	(1.212)
W× InPes					-1.231***	-1.147**	-4.750***	-0.868
					(0.391)	(0.580)	(1.330)	(1.225)
W× InPla					0.253*	0.631***	0.499	0.935*
W× InDie					0.007	0.518	(0.392) -6.688***	0.878
					(0.187)	(0.642)	(1.855)	(0.668)
₩× In <i>Ele</i>					0.073	0.170	1.564	-0.734
					(0.132)	(0.242)	(1.063)	(0.599)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	NO	NO	NO	NO 0.025	Yes	Yes	Yes	Yes
к	0.953	0.892	0.811	0.925	0.867	0.525	0.170	0.398

Table 7. Heterogeneity analysis of different grain varieties.

The White heteroskedasticity-robust standard errors are in parentheses. ***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively. All regressions have 221 observations.

	Table 8. Heterogeneity	/ analysis of different	grain varieties - decom	position results of SDM.
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	Direct effect		Spatial	spillover	Total	Total effect	
Variables	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	
Rice	0.800***	0.269	1.541*	0.856	2.341**	1.051	
Wheat	0.058	0.135	0.568	0.683	0.627	0.692	
Corn	-0.606	0.418	5.772***	1.120	5.166***	1.151	
Soybean	-0.661	0.572	2.080***	0.810	1.420**	0.557	

***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively.

price and distribution of agricultural machinery in Jiangsu Province and the difference in demand caused by the substitution relationship with other agricultural production factors. The spillover effect of agricultural machinery cross-regional

operations had a significant promotion effect on all grain production except wheat. The spatial spillover in the corn production process was greater, indicating that it is easier to increase corn production through agricultural machinery. The total effect performance is basically the same as the spatial spillover.

5.7. Heterogeneity analysis at the regional and temporal levels

To further analyze the threshold effect and spatial spillovers of agricultural mechanization on grain yield in different regions, samples were divided into southern Jiangsu (Sunan), central Jiangsu (Suzhong), and northern Jiangsu (Subei) for comparison. There are substantial differences in agricultural production across the different regions of Jiangsu Province. Sunan has a high level of economic development, a low proportion of agricultural output value, and a small grain-sown area. The economic development level of Subei is relatively low, the agricultural output value accounts for a high proportion, and the grainsown area is large. At the same time, Subei has established a mature cross-region service team for agricultural machinery. Estimating the threshold effects and spatial spillovers of agricultural mechanization level on grain yield by subregion could help to explain the baseline regression results further. Table 9 reports the regression results of the threshold effect and the SDM. As can be seen, the estimated coefficients of agricultural mechanization on grain yield in Column 1 are similar to those in Column 2. Meanwhile, none of the three subregions could pass the single threshold test, which indicates that mechanization had no nonlinear effect on grain yield. It can also be seen from Table 9 that the threshold effect of agricultural mechanization level on grain yield caused by grain-sown area varies greatly among the three regions. The effect of agricultural mechanization on grain yield was negative in Sunan, which had the smallest grain-sown area, indicating that a small grainsown area inhibited the effect of agricultural mechanization on local grain yield. However, in Suzhong, where the grain-sown area is larger, agricultural mechanization had a significant positive impact on local grain yield. Finally, in Subei, which has the largest grain-sown area, agricultural mechanization had no significant effect on the local grain yield, which may be related to the professional farm machinery team providing agricultural machinery services. Therefore, we further focused on the decomposition results of the SDM. The results show that the total effect of agricultural mechanization on grain yield in Sunan was negative, and there was no spatial spillover, which is consistent with the threshold model estimates. The direct effect of agricultural mechanization on grain yield in Suzhong was significantly positive, but there was no spatial spillover. However, in Subei,

Table of neterogeneity analysis at the regional and temporal levels.								
	$\ln Mac(\ln Are < \sigma_1)$	lnMac (InAre≥σ1)	Threshold value	Direct effect	Spatial spillover	Total effect	Mean(InAre)	
Sunan	-0.130**	-0.132**	11.927	-0.087	-0.085	-0.172**	11.944	
	(0.058)	(0.058)	1.680{0.638}	(0.094)	(0.110)	(0.074)	[0,179]	
Suzhong	0.341**	0.342**	12.910	0.156**	-0.161	-0.005	12.992	
	(0.149)	(0.149)	0.900{0.918}	(0.077)	(0.113)	(0.147)	[0.168]	
Subei	0.080	0.079	13.137	0.005	0.121***	0.126	13.311	
	(0.071)	(0.070)	3.260{0.354}	(0.060)	(0.069)	(0.101)	[0.243]	

Table 9. Heterogeneity analysis at the regional and temporal levels.

***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively. The regression standard error is in parentheses, the standard deviation is in brackets, and the p-value of the threshold test is reported in braces.

the spatial spillover of agricultural mechanization on grain yield was significantly positive, which indicates that the development of agricultural mechanization in Subei will significantly increase the grain yield in other regions; this is the positive impact of the specialized agricultural cross-regional service team in Subei. It can be seen that when the supply capacity of agricultural machinery service exceeds the market capacity of this region, crossregional operation may induce the expansion of the service radius, thus producing an increase in grain yield in other regions.

This study also analyzed the heterogeneity of the samples at the temporal level, and the regression results are shown in Figure 5. Figure 5 shows the results of dividing the sample into two segments. There is an obvious threshold effect before 2008, but no obvious threshold effect after 2008. At the same time, before 2008, agricultural mechanization had a significant direct impact on grain yield, but after 2008, the spatial spillover effect of agricultural mechanization on grain yield was positive. In the early stage of the sample, the existence of the threshold effect inhibited the promotion of agricultural mechanization to grain yield. As time progressed to the later stage of the sample, the spatial spillover effect of agricultural mechanization on grain yield became prominent, and the development of cross-regional operations of agricultural machinery makes up for the restrictive effect of grain-sown area on agricultural mechanization. The temporal heterogeneity of the threshold effect and the spatial spillover effect needs to be studied further, but it can be preliminarily found that the threshold effects and the spatial spillovers of agricultural mechanization level on grain yield change with time.

6. Discussions and conclusions

This study constructed a threshold regression model and an SDM, using grain production and agricultural production input factor data from 13 prefecture-level cities in Jiangsu Province from 2000 to 2016, and systematically investigated the threshold effect and the spatial spillover effect of the level of agricultural mechanization on grain production. The results reveal that: (1) The agricultural mechanization level had



Figure 5. Temporal heterogeneity of threshold effects and spatial spillovers. The figure shows the temporal heterogeneity regression results of threshold effect and spatial spillover. The bars represent the magnitude of the estimated coefficients, the black line segments represent confidence intervals, and the colors represent different results. The threshold effect and spatial spillover were significantly different in the pre- and post-sample periods. Source: Calculated by the authors.

a single threshold effect on grain production. When the logarithm of the grain-sown area was less than 12.579, agricultural mechanization had no significant impact on grain production. When the logarithm of the grain-sown area was greater than or equal to 12.579, agricultural mechanization had a significant promoting effect on grain production. (2) The grain yield and the agricultural mechanization level showed a significant spatial correlation, and the global Moran's index of both grain yield and agricultural mechanization level has been above 0.1 for a long time. (3) The agricultural mechanization level had a significant spatial spillover effect on grain production. An increase in agricultural mechanization level in one region would significantly promote grain production in the surrounding regions. It was estimated that every 1% increase in the local agricultural mechanization level would increase grain yield in surrounding cities by 87%. (4) The threshold effect and spatial spillover were heterogeneous among different grain varieties, and the grain-sown area threshold effects are significant in corn and wheat production. The spatial spillover of the mechanization of corn production was relatively high, while the mechanization of wheat production did not exhibit any spatial spillovers.

Our findings have the following policy implications. First, considering the threshold effects of agricultural machinery, developing countries with low mechanization development levels can encourage the development of cross-regional operations to overcome the inhibiting effect on mechanization caused by small grain-sown areas. Second, since the mechanization level has a significant spatial spillover effect on grain production, the government should further strengthen exchanges and cooperation between related departments, as well as the coordination and optimization of agricultural machinery services in the area of resource allocation and industrial distribution. It should also make efforts to further develop agricultural machinery inter-district homework services, which provide good security. The establishment of a unified agricultural machinery cross-regional operation service information platform should be considered, if conditions permit it. Third, countries and regions that already have a cross-regional operation mode of agricultural machinery services can enable this mode to produce wider economic benefits through further specialization and sharing of technical progress. Therefore, we encourage agricultural machinery cross-regional operation services to form industrial clusters, establish and perfect their operation mechanisms, and promote the common development of the whole industry.

This study contributes to research on the effect of agricultural mechanization level on grain production by providing the latest empirical evidence in the case of Jiangsu Province, one of the largest grain production provinces in the world's largest developing country. The nonlinear and spatial effects of agricultural input factors represented by the agricultural mechanization level on grain production were meticulously investigated, and this supplemented the literature on the impact and mechanism of mechanized cross-regional operations in agricultural economics. Furthermore, we obtained the threshold effects and spatial spillovers of agricultural mechanization development level on grain production in the empirical analysis, thus enriching the practical application of production theory in micro-economics and agricultural economics. Finally, our conclusions not only have explanatory power in China, but also contribute to other large agricultural countries and developing countries with similar characteristics. Our study provides a reference for these countries to formulate agricultural mechanization development strategies to plan and adjust agricultural production strategies according to local conditions. Meanwhile, this study will

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contribute to the promotion of social stability in developing countries, since the issue of food security is of great significance in this regard.

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Appendix

	Grouped regression					
	of In <i>Mac</i>		SLM	SAR	Unrobust SE	0–1 Matrix
	Model 21	Model22	Model 23	Model 24	Model 25	Model 26
Variables	(1)	(2)	(3)	(4)	(5)	(6)
In <i>Mac</i>	-0.116*	0.089**	0.051**	0.058	0.020	0.029
	(0.043)	(0.035)	(0.020)	(0.031)	(0.028)	(0.025)
In <i>Are</i>	1.114***	1.325***	1.051***	0.832***	0.953***	1.030***
	(0.076)	(0.096)	(0.047)	(0.047)	(0.040)	(0.038)
In <i>Fer</i>	0.036	-0.053	0.049	0.087	0.0199	-0.005
	(0.144)	(0.074)	(0.046)	(0.073)	(0.037)	(0.032)
ln <i>Lab</i>	0.097	-0.022	-0.060***	-0.012	-0.049**	-0.061***
	(0.124)	(0.016)	(0.015)	(0.015)	(0.023)	(0.020)
In <i>Pes</i>	-0.137**	0.050	0.033	0.001	0.056**	0.045**
	(0.048)	(0.047)	(0.028)	(0.031)	(0.027)	(0.023)
In <i>Pla</i>	0.034	0.067	0.009	-0.000	-0.009	0.001
	(0.023)	(0.036)	(0.013)	(0.021)	(0.014)	(0.012)
In <i>Die</i>	0.157	0.017	0.040	0.043	0.031	0.037**
	(0.077)	(0.043)	(0.026)	(0.025)	(0.023)	(0.018)
In <i>Ele</i>	0.043	0.004	0.041***	0.023	0.042***	0.036**
	(0.035)	(0.015)	(0.014)	(0.010)	(0.015)	(0.014)
W× In <i>Yie</i>				0.506***	0.722***	0.747***
				(0.066)	(0.054)	(0.037)
W× In <i>Mac</i>					0.242**	0.042
					(0.102)	(0.037)
W× InAre					-0.496***	-0.774***
					(0.120)	(0.064)
W× InFer					-0.125	-0.025
					(0.144)	(0.063)
₩× In <i>Lab</i>					0.249***	0.072***
					(0.084)	(0.027)
W× InPes					-0.033	-0.050
					(0.078)	(0.039)
W× In <i>Pla</i>					-0.003	0.024*
					(0.065)	(0.014)
W× InDie					-0.191*	-0.069**
					(0.109)	(0.033)
W× In <i>Ele</i>					0.039	-0.034**
					(0.045)	(0.017)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Observations	85	136	221	221	221	221
K⁴	0.919	0.913	0.896	0.909	0.919	0.911

Table A1. Robustness check I – regression estimation results.

The White heteroskedasticity-robust standard errors are in parentheses. ***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively. All regressions have 221 observations.

	Direct	Direct effect Spatial spillover		Total effect		
Variables	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
Model 24						
In <i>Mac</i>	0.061*	0.033	0.055*	0.029	0.116*	0.060
In <i>Are</i>	0.869***	0.044	0.822***	0.215	1.691***	0.225
In <i>Fer</i>	0.096	0.076	0.091	0.078	0.187	0.151
In <i>Lab</i>	-0.013	0.015	-0.012	0.015	-0.025	0.030
In <i>Pes</i>	-0.002	0.031	0.001	0.031	-0.001	0.062
In <i>Pla</i>	0.002	0.023	-0.000	0.023	0.001	0.045
In <i>Die</i>	0.045*	0.025	0.044	0.029	0.089*	0.052
In <i>Ele</i>	0.023	0.011	0.022*	0.013	0.044*	0.023
Model 25						
In <i>Mac</i>	0.079*	0.042	0.915**	0.431	0.995**	0.462
In <i>Are</i>	0.991***	0.041	0.625**	0.266	1.616***	0.280
In <i>Fer</i>	0.001	0.062	-0.358	0.583	-0.357	0.637
ln <i>Lab</i>	-0.006	0.032	0.689**	0.299	0.683**	0.325
In <i>Pes</i>	0.057	0.038	0.041	0.312	0.098	0.342
In <i>Pla</i>	-0.010	0.024	-0.021	0.242	-0.031	0.263
In <i>Die</i>	-0.008	0.045	-0.617	0.447	-0.625	0.489
In <i>Ele</i>	0.056***	0.02	0.219	0.155	0.274	0.169
Model 26						
In <i>Mac</i>	0.059*	0.033	0.229*	0.132	0.288*	0.155
In <i>Are</i>	1.024***	0.041	-0.032	0.142	0.992***	0.163
In <i>Fer</i>	-0.012	0.054	-0.087	0.258	-0.100	0.306
In <i>Lab</i>	-0.051**	0.024	0.083	0.093	0.032	0.109
In <i>Pes</i>	0.036	0.032	-0.057	0.150	-0.021	0.175
In <i>Pla</i>	0.013	0.016	0.088	0.055	0.101	0.068
In <i>Die</i>	0.018	0.029	-0.148	0.133	-0.130	0.159
In <i>Ele</i>	0.032**	0.016	-0.026	0.052	0.007	0.061

Table A2. Robustness check II – decomposition results.

***, ** and * mean significant effects of the variables at 1%, 5% and 10% levels, respectively; the results of SLM cannot be decomposed.



Figure A1. LR statistics for threshold test. The figure shows the LR statistics for the single threshold test. There is a single threshold in Model 12, which is 12.579.Source: Produced by the authors.