

Article

Production-Dependent Effects of Agricultural Mechanization on Rural Income: Evidence from China

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Abstract

This study examines whether agricultural mechanization promotes rural income growth in China. Using provincial panel data from 2000–2023, a two-way fixed effects model and a Spatial Durbin Model (SDM) are employed to estimate the direct, conditional, and spatial effects of mechanization. The results show that the positive association between mechanization and rural income becomes statistically insignificant after controlling for agricultural production, while agricultural production remains significantly associated with rural income. Mechanization exhibits diminishing returns as production levels increase and appears to be more effective in grain-oriented agricultural systems. Spatial analysis further reveals that agricultural production generates significant spillover effects, whereas mechanization itself does not. This study contributes to the literature by distinguishing the income effect of mechanization from its production-related and spatial effects. The findings suggest that policies should focus on strengthening production capacity, improving agricultural service systems, and better aligning mechanization investment with regional production structures.

Keywords: agricultural production; spatial dependence; regional heterogeneity; mechanization allocation; Spatial Durbin model

1. Introduction

1.1. Background

As China's agriculture enters a stage of high-quality development, improving productivity and increasing farmers' income have become central policy priorities. However, agricultural profitability has been continuously compressed, largely due to rising input costs and structural distortions associated with subsidy policies, which have weakened the competitiveness of agricultural products. Empirical evidence shows that the net profit of major grain crops has shifted from positive to negative over the past decade, highlighting the growing mismatch between production costs and output value. Meanwhile, China's agricultural system remains dominated by smallholder farming, where fragmented land and limited technology adoption constrain efficiency gains and income growth [1]. These challenges underscore the need to accelerate agricultural mechanization and enhance the role of technological upgrading.

Agricultural mechanization is widely regarded as a key driver of productivity growth and structural transformation. However, its adoption in developing countries is often constrained by small-scale farming and imperfect factor markets, resulting in lower capital



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intensity compared to developed economies [2,3]. Although existing studies have primarily focused on the productivity effects of mechanization [4], its role in shaping rural income remains less clear, particularly under heterogeneous production conditions and spatial interactions. Therefore, this study asks: Does agricultural mechanization contribute to rural income growth, and if so, through what transmission channels and under what conditions?

1.2. Literature Review

1.2.1. Agricultural Mechanization, Production, and Rural Income

Agricultural mechanization has become a central topic in the literature on agricultural mechanization, rural transformation, and sustainable development. Existing studies increasingly suggest that mechanization should not be understood as a universally effective technological input, but rather as a production-embedded and regional development conditions [2,3]. Existing studies generally agree that mechanization is not merely a technical substitution of machinery for labor, but a broader structural force that reshapes production efficiency, factor allocation, environmental outcomes, and rural welfare [1]. However, although the spatial literature documents significant regional spillovers in agricultural systems, existing studies rarely distinguish whether such spillovers originate from mechanization itself or from broader agricultural production linkages. As a result, the relative spatial role of mechanization and production in shaping rural income remains unclear. Reviewing these strands together helps clarify an important unresolved question, whether mechanization directly increases rural income, or whether its income effect depends on production conditions, agricultural structure, and spatial context.

First, a large body of research emphasizes the contribution of agricultural mechanization to production growth and modernization. At the production level, mechanization is widely associated with higher operational efficiency, improved factor allocation, and stronger production capacity. Evidence from Nigeria shows that mechanization affects not only productivity but also economies of scope across crop categories, suggesting that machinery use can reshape the internal organization of farm production rather than simply replace labor [5]. In China, full mechanization has been shown to increase agricultural production while also generating environmental co-benefits, including reductions in straw burning and PM2.5 emissions. These effects are stronger in areas with flatter terrain, more concentrated farmland, and greater use of medium- and large-scale machinery [6]. Existing studies generally support a positive relationship between mechanization and rural welfare. However, it remains unclear whether mechanization affects rural income directly or mainly through agricultural production.

1.2.2. Production Conditions and Structural Heterogeneity

At the same time, the literature also indicates that the effects of mechanization are conditioned by land institutions, production organization, and rural structural change. In hilly and mountainous areas, land fragmentation remains a major obstacle to machinery use, and land consolidation suitable for agricultural machinery is considered a critical pathway to improving productivity and sustainable land use [7]. Similarly, studies on farmland abandonment in mountainous China show that better mechanization conditions can significantly reduce abandonment, although these effects interact with crop choice and household characteristics [8]. Evidence from rural China further suggests that capital entering the countryside can reduce cropland abandonment partly by enhancing mechanization and agricultural productive services [9]. A related line of research conceptualizes land consolidation itself as a form of technical change, showing that it can increase machinery use, raise farm productivity and income, and release labor to off-farm employment [10].

These findings suggest that the effectiveness of mechanization may depend on production conditions and agricultural structure rather than being uniform across regions.

1.2.3. Spatial Spillovers in Agricultural Development

Secondly, this study is primarily grounded in the framework of spatial economics and spatial econometrics. Within this tradition, economic outcomes are viewed as spatially interdependent, such that activities in one region may influence neighboring regions through market integration, factor mobility, technology diffusion, and production linkages. In agricultural systems, such interdependence may arise through market integration, factor mobility, technology diffusion, and production linkages. Recent studies have increasingly applied spatial econometric approaches to agricultural and environmental issues. For example, Malaekhe et al. [11] show that failing to account for spatial spillovers leads to misspecified estimates of climate-change impacts on agricultural revenues. Li et al. [12] further demonstrate that agricultural economic growth exhibits significant spatial agglomeration and that spatial econometric models provide a useful framework for identifying regional spillover effects. These studies suggest that agricultural outcomes should be analyzed within a spatially interconnected system rather than as purely local processes.

An important strand of the literature highlights that agricultural production and mechanization are spatially embedded processes. Rather than being confined to local administrative units, agricultural outcomes are often shaped by regional interaction, spatial dependence, and cross-regional service flows. Several recent studies directly document the presence of spatial spillover effects in agricultural systems. Wu et al. show that agricultural mechanization has both threshold effects and significant spatial spillover effects on grain production, implying that mechanization in one region can raise grain yield in neighboring regions through cross-regional machinery operation [13]. Similarly, Fang et al. finds that agricultural mechanization improves the climate resilience of food production not only locally but also in surrounding provinces, with the spillover effect mainly transmitted through cross-latitude harvesting services [14]. Research on grain productivity also confirms that agricultural machinery can generate positive spatial spillovers, especially in major grain-producing regions, where trans-regional machinery operations and low-carbon practices strengthen the green total factor productivity of grain production [15].

This spatial perspective is reinforced by a broader set of studies on agricultural development, resource use, and regional inequality. Digital technology, for example, has been found to promote agricultural production agglomeration through land transfer and rural human capital accumulation, while also generating significant spatial spillovers with clear regional heterogeneity [16]. Research on agricultural non-point source pollution in the Huang-Huai-Hai Plain likewise shows strong spatial heterogeneity and spillover effects in the drivers of pollution, underlining the need to analyze agricultural systems in a regionally coordinated framework [17]. Similar evidence is found in studies of agricultural carbon emission efficiency, where spatial Durbin models reveal nonlinear direct and indirect effects of machinery deployment, irrigation, fertilizers, and pesticides, with local benefits often coexisting with negative externalities in adjacent regions [18]. Beyond agriculture narrowly defined, research on township economic landscapes in China demonstrates that rural–urban income inequality is strongly shaped by spatial heterogeneity in local economic structure, urbanization, and industrial development [19]. Together, these studies imply that rural income and agricultural mechanization should be analyzed as outcomes embedded in spatially interconnected regional systems rather than as purely local processes. Although existing studies document substantial spatial spillovers in agricultural systems, limited attention has been paid to whether rural income spillovers are driven primarily by mechanization itself or by broader agricultural production linkages.

Third, a growing body of literature examines the relationship between agricultural mechanization and rural income, poverty reduction, and household welfare. Much of this literature finds that mechanization contributes positively to farm income and broader rural welfare, but the causal channels are more complex than a simple direct effect. Using household survey data from Hubei, show that higher mechanization levels significantly increase crop output, operating income, and returns, and that these effects are mediated through factor intensification and quality improvement [20]. Evidence from Pakistan similarly suggests that full mechanization substantially raises farm income and food security compared with semi-mechanized production strategies [21]. Beyond direct ownership of machinery, agricultural mechanization services also appear to play an important role in inclusive rural development. Qiu et al. find that adopting agricultural machinery socialization services can reduce relative poverty among farmers, mainly through improvements in human capital such as skills training and non-farm work experience [22]. Sang et al. further show that mechanization services increase household income and help narrow the rural income gap, especially among lower- and middle-income groups and in eastern and western China [23]. Cross-country case evidence likewise suggests that scaling mechanization service provision is crucial in smallholder systems, although its long-term effectiveness depends on finance, coordination, and service ecosystem development [24].

Research on rural transformation and farmland use transition also suggests that higher rural income, labor outmigration, and non-agricultural employment reshape agricultural land use and mechanization patterns simultaneously [25]. Moreover, Zou et al. provide a cautionary result by showing that agricultural mechanization may even reduce local GDP under certain conditions by lowering agricultural output value, reducing local labor demand, and crowding out consumption and local service-sector development [26]. Related studies on cluster farming and local production organization also indicate that increases in productivity and income depend heavily on management quality, institutional coordination, and market access rather than on technology alone [27]. Thus, while the literature generally supports a positive association between mechanization and rural welfare, it also suggests that the magnitude, direction, and transmission pathways of this relationship depend on production conditions, service systems, and local structural contexts.

Despite these advances, three important gaps remain. First, existing studies rarely distinguish whether mechanization affects rural income directly or primarily through agricultural production. Second, limited attention has been paid to whether the effectiveness of mechanization depends on production conditions and agricultural structure. Third, although spatial spillovers have been widely documented, few studies directly compare the spillover roles of mechanization and agricultural production in shaping rural income. Addressing these gaps provides the foundation for the hypotheses and empirical strategy developed in this study.

To address these gaps, this study treats agricultural mechanization as a condition-dependent factor rather than a uniformly effective technology. The analysis focuses on whether mechanization improves rural income directly or mainly through agricultural production. It further examines how the effectiveness of mechanization varies across different production structures and agricultural systems. Using provincial panel data from China, this study combines fixed-effects models, spatial econometric analysis, and instrumental-variable estimation to examine the relationship between mechanization, agricultural production, and rural income. By doing so, the study contributes to the literature in three ways. First, it distinguishes the production effect of mechanization from its income effect. Second, it examines whether the effectiveness of mechanization varies across different agricultural structures and production systems. Third, it compares the spatial spillover role of mechanization with that of agricultural production in shaping rural income dynamics.

2. Hypotheses Development

Agricultural mechanization is generally viewed as a productivity-enhancing capital input that improves operational efficiency and production capacity [5,6,28]. However, machinery use does not automatically translate into higher rural income. The income benefits of mechanization depend on whether efficiency gains can be transformed into agricultural output and subsequently realized through markets. Existing evidence further suggests that mechanization contributes to income through output expansion, factor intensification, and production improvement rather than through machinery use alone [20]. Therefore, mechanization is more likely to influence rural income through agricultural production than through a purely direct channel.

H1. *Agricultural mechanization affects rural income mainly through agricultural production rather than through an independent direct channel.*

The effectiveness of mechanization is also likely to depend on production conditions. Previous studies show that land fragmentation, terrain constraints, and insufficient supporting services can reduce the productivity benefits of machinery, whereas land consolidation and agricultural services can improve mechanization efficiency through scale economies [7–10]. Consequently, mechanization may generate larger marginal benefits in less-developed production environments but smaller incremental gains in regions where production systems are already highly mechanized and productive.

H2. *The income effect of agricultural mechanization depends on agricultural production conditions and weakens as agricultural production levels increase.*

Agricultural structure may further influence the effectiveness of mechanization. Grain-oriented production systems are generally more standardized and compatible with mechanized operations, whereas diversified non-grain systems often involve greater production heterogeneity and stronger reliance on labor-intensive management. Existing studies indicate that mechanization tends to perform more effectively in grain-production systems and may generate stronger threshold and spillover effects in such contexts [13–15].

H3. *Agricultural mechanization has a stronger positive effect on rural income in grain-oriented agricultural systems than in diversified non-grain agricultural systems.*

Finally, agricultural development is embedded within a spatially interconnected regional economy. Spatial studies suggest that mechanization, agricultural production, and related development processes may exhibit spatial dependence and spillover effects [13,19]. However, mechanization remains relatively location-specific because its effectiveness depends on local production conditions, whereas agricultural production may influence neighboring regions through market integration, supply chains, and output linkages. Therefore, agricultural production is expected to generate broader regional spillovers than mechanization itself.

H4. *Agricultural production generates stronger spatial spillover effects on rural income than agricultural mechanization itself.*

3. Materials and Methods

3.1. Workflow

The workflow of this study is presented in Figure 1. First, provincial panel data for China from 2000 to 2023 are collected and processed. Main continuous variables are trans-

formed into logarithmic form where appropriate. Second, a two-way fixed effects model is estimated to examine the relationship between agricultural mechanization and rural income while controlling for province and year fixed effects. Third, interaction terms are introduced to test whether the effect of mechanization depends on agricultural production conditions and grain-oriented agricultural structure. Fourth, spatial dependence is examined using Moran's I statistics and LISA analysis. A Spatial Durbin Model (SDM) is then employed to estimate direct effects and spatial spillover effects. Fifth, an instrumental-variable approach based on diesel-price-induced variation in mechanization costs is adopted to alleviate potential endogeneity concerns. Finally, a series of robustness and heterogeneity analyses, including alternative specifications, placebo tests, and subgroup analysis, are conducted to verify the stability of the results.

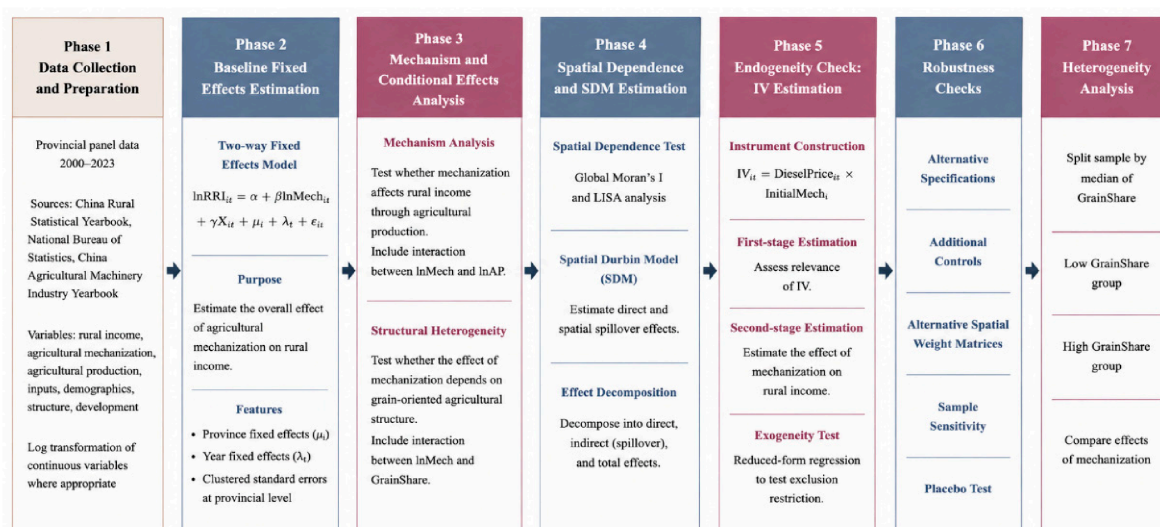


Figure 1. The workflow of this study.

Figure 1 summarizes the empirical strategy used to examine the relationship between agricultural mechanization, agricultural production, and rural income. The workflow links the study's hypotheses concerning production-conditioned effects (H1–H3) and spatial spillovers (H4) to the corresponding econometric methods, including fixed-effects models, interaction analyses, spatial econometric models, and robustness tests.

3.2. Dataset

This study employs a balanced provincial panel dataset covering 31 provinces in China over the period 2000–2023. The dataset is constructed from multiple official statistical sources, including the China Rural Statistical Yearbook, China Statistical Yearbook, China Price Statistical Yearbook, and the China Agricultural Machinery Industry Yearbook. These data provide comprehensive information on rural income, agricultural production, mechanization, and regional socioeconomic characteristics, ensuring consistency and reliability across provinces and over time (Table 1).

The dependent variable is rural residents' per capita disposable income (RRI), which captures the level of rural economic welfare. The key explanatory variable is agricultural mechanization (MechIndex), measured as the ratio of total agricultural machinery power to crop sown area. Control variables are selected to account for production conditions, demographic factors, and regional development, including agricultural production (AP), rural population (RP), primary industry share (PrIndShare), diesel price (DP), rural electricity consumption (RE), fertilizer use (Fert), planting area (PA), grain structure (GrainShare), and gross domestic product (GDP). All variables are defined at the provincial level, forming

a long-term panel dataset that allows for the analysis of both temporal dynamics and spatial interactions.

Table 1. Variable definitions and data sources.

Variable	Symbol	Role	Source
Rural resident income	RRI	Dependent variable	China Rural Statistical Yearbook
Agricultural mechanization	MechIndex	Key explanatory variable	Calculated from MP and SA; China Rural Statistical Yearbook
Diesel price	DP	Control variable	China Price Statistical Yearbook/National Bureau of Statistics
Primary industry share	PrIndShare	Control variable	China Statistical Yearbook
Rural population	RP	Control variable	China Rural Statistical Yearbook
Agricultural production	AP	Control variable	China Rural Statistical Yearbook
Rural electricity consumption	RE	Control variable	China Rural Statistical Yearbook
Fertilizer use	Fert	Agricultural input variable	China Rural Statistical Yearbook
Planting area	PA	Agricultural scale variable	China Rural Statistical Yearbook
Crop sown area	SA	Agricultural scale variable	China Rural Statistical Yearbook
Grain sown area	GA	Agricultural structure variable	China Rural Statistical Yearbook
Grain area ratio	Grainshare	Agricultural input variable	Calculated from GA and SA; China Rural Statistical Yearbook
Machinery power	MP	Mechanization component variable	China Rural Statistical Yearbook/China Agricultural Machinery Industry Yearbook
Gross Domestic Product	GDP	Regional economic variable	China Statistical Yearbook
Grain production	GP	Control variable	China Rural Statistical Yearbook
Grain production/Per	GPP	Control variable	China Rural Statistical Yearbook

All regression models include year fixed effects, which absorb common nationwide inflationary shocks and macroeconomic price-level changes over time. Therefore, the estimated relationships are identified primarily from cross-provincial variation and within-province changes beyond aggregate national trends.

3.3. Two-Way Fixed Effects Model

To examine the impact of agricultural mechanization on rural income, this study first employs a two-way fixed effects (TWFE) model using provincial panel data. The baseline specification is given as follows:

$$\ln RRI_{it} = \beta_0 + \beta_1 \ln Mech_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t denote province and year, respectively. $\ln RRI_{it}$ represents the logarithm of rural residents' per capita disposable income, and $\ln Mech_{it}$ denotes the level of agricultural mechanization. X_{it} is a vector of control variables, including agricultural production, rural population, industrial structure, input factors, and regional economic conditions. μ_i captures unobserved province-specific effects that are time-invariant, such as geographic

conditions and institutional characteristics, while λ_t controls for common time effects, including macroeconomic shocks and nationwide policy changes. ε_{it} is the error term.

The two-way fixed effects model is adopted to address potential omitted variable bias arising from both cross-sectional heterogeneity and time-specific shocks. Standard errors are clustered at the provincial level to account for serial correlation and heteroskedasticity. This specification allows for a consistent estimation of the relationship between agricultural mechanization and rural income by isolating within-province variation over time.

3.4. Interaction and Conditional Effects Models

To examine whether the effectiveness of mechanization depends on production conditions and agricultural structure, interaction terms are introduced into the baseline fixed-effects framework. Specifically, the interaction between mechanization and agricultural production is estimated to test whether the marginal effect of mechanization varies across production levels. In addition, an interaction between mechanization and grain-production share is included to examine whether mechanization performs differently in grain-oriented and non-grain agricultural systems.

The general specification is Equation (2):

$$\ln RRI = \beta_0 + \beta_1 \ln Mech + \beta_2 Z + \beta_3 (\ln Mech \times Condition) + \mu + \lambda + \varepsilon \quad (2)$$

where *Condition* represents either agricultural production *lnAP* or grain-production share *GrainShare*, depending on the specification. Province fixed effects (μ) and year fixed effects (λ) are included to control for unobserved heterogeneity across provinces and over time.

3.5. Instrumental Variable Strategy

To alleviate potential endogeneity concerns arising from reverse causality and omitted variables, an instrumental-variable approach is employed. The instrument is constructed as the interaction between provincial diesel prices and historical mechanization dependence. Because diesel fuel is a major operating input for agricultural machinery, changes in diesel prices affect mechanization costs, while provinces with different levels of historical mechanization dependence are expected to respond differently to such cost shocks.

The first-stage equation is specified as Equation (3).

$$\ln Mech = \pi_0 + \pi_1 IV + \pi_2 X + \mu + \lambda + v \quad (3)$$

where *IV* denotes the interaction between diesel prices and historical mechanization dependence, *X* represents the set of control variables, μ denotes province fixed effects, λ denotes year fixed effects, and v is the error term. The predicted values of mechanization from the first stage are then used in the second-stage rural income equation.

3.6. SDM

Given the potential spatial dependence of rural income across regions, this study further employs a Spatial Durbin Model (SDM) to capture both direct and spillover effects of agricultural mechanization. The use of spatial econometric models is motivated by the fact that economic activities in one province may influence neighboring regions through factor mobility, market integration, and policy diffusion. Ignoring such spatial interactions may lead to biased and inconsistent estimates. The baseline spatial weight matrix is constructed using provincial geographic contiguity and is row-standardized so that the weights associated with each province sum to one. This specification reflects the expectation that agricultural production, machinery services, technology diffusion, and factor mobility are more likely to occur between geographically adjacent provinces. As a robustness check,

an inverse geographic distance matrix is also employed to capture spatial interactions that may decline gradually with distance rather than being restricted to direct neighbors.

The baseline SDM specification is given as follows:

$$\ln RRI_{it} = \rho W \ln RRI_{it} + \beta_1 \ln Mech_{it} + \theta W \ln Mech_{it} + \gamma X_{it} + \delta W X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where W denotes the spatial weight matrix, which captures the spatial structure between provinces, and $W \ln RRI_{it}$ represents the spatial lag of the dependent variable, reflecting endogenous interaction effects. The coefficient ρ measures the degree of spatial dependence in rural income. $W \ln Mech_{it}$ and $W X_{it}$ denote the spatial lags of the explanatory and control variables, capturing exogenous spillover effects from neighboring regions.

Compared with simpler spatial models such as the Spatial Autoregressive Model (SAR) or Spatial Error Model (SEM), the SDM is more flexible, as it allows for both endogenous and exogenous spatial interactions. This is particularly suitable in the context of agricultural development, where both the outcomes (income) and the determinants (mechanization, production, inputs) may exhibit spatial spillovers. Following standard practice, the SDM is estimated with province and year fixed effects to control for unobserved heterogeneity. To facilitate interpretation, the estimated coefficients are further decomposed into direct effects, indirect effects (spatial spillovers), and total effects. The direct effect reflects the impact of mechanization within a province, while the indirect effect captures how changes in one province affect rural income in neighboring provinces through spatial linkages.

3.7. Robustness Test

As an additional robustness check, this study constructs an economic-distance spatial weight matrix based on similarities in provincial economic development levels. Specifically, the spatial weight between provinces i and j is defined as:

Spatial dependence is modeled using a row-standardized contiguity-based spatial weight matrix, where provinces sharing a common border are treated as neighbors. This specification is appropriate in the context of agricultural development because agricultural production, machinery services, technology diffusion, and factor mobility are more likely to occur between geographically adjacent provinces. To examine the robustness of the spatial results, this study further employs alternative spatial weight matrices, including an inverse geographic distance matrix and an economic-distance matrix based on provincial GDP per capita similarity. Consistent results across alternative specifications would suggest that the main findings are not sensitive to the definition of spatial connectivity.

$$w_{ij} = \frac{1}{|GDPpc_i - GDPpc_j|} \quad (5)$$

where $GDPpc_i$ and $GDPpc_j$ denote GDP per capita in provinces i and j , respectively. Provinces with more similar levels of economic development are assigned larger spatial weights, reflecting the possibility that regions at comparable development stages may exhibit stronger interactions through agricultural markets, technology diffusion, production organization, and factor mobility. To ensure comparability with the baseline specification, the matrix is row-standardized so that the weights associated with each province sum to one.

Compared with geographic contiguity and inverse-distance matrices, the economic-distance matrix captures spatial linkages arising from economic similarity rather than physical proximity. This provides an additional robustness test of whether the estimated spatial effects depend on the definition of interprovincial connectivity. Lastly, to improve

transparency and consistency, all variable definitions, model notation, and empirical specifications are standardized throughout the manuscript.

4. Results

This section presents the empirical results of the analysis. The discussion begins with the baseline estimates from the two-way fixed effects model, followed by specifications that incorporate additional control variables to examine potential transmission channels. Spatial dependence is then assessed, and the Spatial Durbin Model (SDM) is employed to capture both direct and spillover effects. Finally, interaction effects and robustness checks are conducted to evaluate the consistency and reliability of the results.

4.1. Variables Correlation Analysis and Description Statistics

Table 2 outlines the descriptive statistics for all variables used in this study. Table 3 presents the spearman correlation matrix for the main variables used in this study. The correlation analysis provides a preliminary understanding of the relationships among agricultural mechanization, rural income, and other control variables, and helps to identify potential multicollinearity issues before conducting the regression analysis. Based on statistics, rural income is strongly correlated with GDP (0.773) and rural electricity consumption (0.489). These results indicate that regional economic development and agricultural infrastructure play important roles in shaping rural income levels. Meanwhile, the share of the primary industry in GDP is negatively correlated with rural income (-0.626), reflecting that regions with a higher reliance on primary industries tend to have lower income levels. It is also worth noting that several agricultural scale variables exhibit relatively high correlations. For instance, planting area, fertilizer use, agricultural output, and machinery power are highly correlated with each other, indicating that these variables may capture similar aspects of agricultural production scale. To avoid potential multicollinearity problems in the regression analysis, these variables are not simultaneously included in the baseline model. Based on these considerations, the empirical analysis employs agricultural mechanization as the core explanatory variable and selects a set of control variables capturing industrial structure, rural population, agricultural inputs, and regional development. A two-way fixed effects model with province and year fixed effects is then estimated to examine the impact of agricultural mechanization on rural income while controlling for unobserved heterogeneity across provinces and over time. No correlation coefficient exceeds the conventional threshold that would indicate severe multicollinearity.

Table 2. Variables and definitions.

Variable	Definition
Diesel price (DP)	Average price of agricultural diesel fuel each province
Planting area (PA)	Total agricultural planting area, indicating the overall scale of agricultural land use
Rural residence income (RRI)	Per capita disposable income of rural residents, used as the dependent variable to measure rural economic welfare
Primary industry share (PrIndShare)	Share of primary industry value added in regional GDP, reflecting the importance of agriculture in the regional economic structure
Rural population (RP)	Total rural population, measured in ten thousand persons
Agricultural production (AP)	Gross output value of agriculture, forestry, animal husbandry and fishery, representing the overall level of agricultural production
Rural electricity consumption (RE)	Total electricity consumption in rural areas, reflecting rural production and living energy demand

Table 2. Cont.

Variable	Definition
Fertilizer use (Fert)	Total of fertilizer production and use, used as a proxy for agricultural input intensity
Agricultural mechanization (MechIndex)	Level of agricultural mechanization measured by the ratio of total agricultural machinery power to total crop sown area (Machinery power/Crop sown area), reflecting the degree of agricultural mechanization
Machinery power (MP)	Total power of agricultural machinery, indicating the level of mechanized agricultural equipment
Crop sown area (SA)	Total sown area of crops in a given year
Grain sown area (GA)	Total sown area of grain crops
Gross Domestic Product (GDP)	Gross Domestic Product, reflecting the level of regional economic development
Grain area ratio (Grainshare)	Ratio of grain sown area to total crop sown area (Grain sown area/Crop sown area), reflecting the structure of crop planting
Grain production	Main agricultural product planting area and output—Total grain output (10,000 tons)
Grain production/Per	Grain yield per unit area

Table 3. Correlation statistics between all variables.

Variables	DP	PA	RRI	PrIndShare	RP	AP	RE	Fert	MechIndex	MP	SA	GA	GDP	Grainshare
Diesel price	1													
Planting area	0.028	1												
Rural resident income	0.617	−0.043	1											
Primary industry share	−0.314 **	0.341 **	−0.626 **	1										
Rural population	−0.186 **	0.765 **	−0.262 **	0.284 **	1									
Agricultural production	0.387 **	0.749 **	0.466 **	−0.012	0.557 **	1								
Rural electricity	0.250 **	0.417 **	0.489 **	−0.418 **	0.506 **	0.723 **	1							
Fertilizer use	0.083 *	0.903 **	0.057	0.177 **	0.780 **	0.814 **	0.598 **	1						
Agricultural mechanization	0.353 **	−0.171 **	0.494 **	−0.466 **	−0.174 **	0.139 **	0.219 **	−0.029	1					
Machinery power	0.217 **	0.895 **	0.192 **	0.109 **	0.696 **	0.866 **	0.601 **	0.903 **	0.169 **	1				
Crop sown area	0.028	1.000 **	−0.043	0.341 **	0.765 **	0.749 **	0.417 **	0.903 **	−0.171 **	0.895 **	1			
Grain sown area	0.012	0.962 **	−0.064	0.290 **	0.716 **	0.681 **	0.379 **	0.857 **	−0.154 **	0.871 **	0.962 **	1		
GDP	0.487 **	0.362 **	0.773 **	−0.539 **	0.295 **	0.770 **	0.848 **	0.509 **	0.320 **	0.560 **	0.362 **	0.323 **	1	
Crop area ratio	−0.035	0.296 **	−0.119 **	0.035	0.069	0.067	−0.060	0.206 **	0.006	0.284 **	0.296 **	0.507 **	−0.066	1

(Notes: ** and * indicate the correlation is significant at the 0.01 level (two-tailed) and the 0.05 level (two-tailed), respectively.).

4.2. Baseline Fixed Effects Regression Results

To examine the relationship between agricultural mechanization and rural income, this study estimates a two-way fixed effects model using provincial panel data. The baseline specification is given as follows:

$$\ln RRI_{it} = \alpha + \beta_1 \ln MechIndex_{it} + \gamma_1 Z_{it} + \gamma_2 I_{it} + \gamma_3 P_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

where i and t denote province and year, respectively. RRI_{it} represents rural residents' per capita disposable income, and $MechIndex_{it}$ measures the intensity of agricultural mechanization. Z_{it} and P_{it} represent structural variables, input variables, and production variables, respectively. Specifically,

$$\begin{aligned} Z_{it} &= \{\ln PrIndShare_{it}, \ln RP_{it}, CrainShare_{it}\} \\ I_{it} &= \{\ln RE_{it}, \ln Fert_{it}\} \\ P_{it} &= \{\ln AP_{it}\} \end{aligned} \quad (7)$$

Province fixed effects (μ_i) and year fixed effects (λ_t) are included to control for unobserved heterogeneity across provinces and common time shocks. Standard errors are clustered at the provincial level.

Table 4 reports the baseline fixed effects estimation results. Column (1) includes only the key explanatory variable. The results show that agricultural mechanization is positively associated with rural income, with an estimated elasticity of approximately 0.12, and the coefficient is statistically significant at the 1% level. The relatively high within R^2 values, particularly in specifications including agricultural production and regional economic controls, partly reflect the inclusion of province and year fixed effects as well as the long-run nature of the provincial panel. These variables capture substantial variation associated with persistent provincial development patterns and common national trends over time.

Table 4. Baseline Fixed Effects Regression Results.

Variables	(1) Baseline	(2) + Structure	(3) + Inputs	(4) + Production
lnMech	0.1208 *** (0.0320)	0.0768 ** (0.0326)	0.0331 (0.0254)	0.0234 (0.0218)
lnAP				0.1608 *** (0.0253)
PrIndShare		−0.0083 ** (0.0032)	−0.0074 *** (0.0024)	−0.0105 *** (0.0024)
lnRP		0.0478 (0.0841)	0.0203 (0.0686)	0.0795 (0.0672)
Grainshare		−0.0523 (0.1916)	−0.0411 (0.1616)	0.1529 (0.1375)
lnRE			0.0246 (0.0155)	0.0088 (0.0121)
lnFert			0.1289 *** (0.0339)	0.0226 (0.0281)
Constant	8.9346 *** (0.0204)	8.6886 *** (0.6321)	8.1377 *** (0.4910)	— —
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	744	744	744	744
R² (within)	0.1136	0.2076	0.3468	0.9967

Notes: All models include province and year fixed effects. Robust standard errors clustered at the provincial level are reported in parentheses. Column (1) includes only mechanization. Column (2) adds structural variables. Column (3) further includes input variables. Column (4) additionally controls for agricultural production. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Column (2) adds structural variables. The coefficient on mechanization decreases but remains statistically significant, suggesting that part of the observed relationship is related to differences in regional economic structure and crop composition.

Column (3) further incorporates input variables, including fertilizer use and rural electricity consumption. After controlling for these factors, the coefficient on mechanization becomes statistically insignificant. This indicates that the positive association observed in simpler specifications is not robust once production inputs are taken into account. In

practical terms, this suggests that expanding machinery investment alone may not be sufficient to improve rural income if production capacity does not increase simultaneously.

Column (4) additionally includes agricultural production. The results show that agricultural production has a strong and statistically significant positive effect on rural income, while the coefficient on mechanization remains insignificant. This finding suggests that agricultural production, rather than mechanization itself, plays a dominant role in determining rural income.

Overall, the results indicate that the apparent income effect of agricultural mechanization is largely driven by omitted variables related to input intensity and production capacity. Once these factors are controlled for, the independent contribution of mechanization becomes weak and statistically insignificant.

This pattern raises an important question: why does agricultural mechanization fail to generate stable income gains? The following section explores the underlying transmission channels, focusing on agricultural structure and production dynamics.

4.3. Mechanism and Conditional Effects Analysis

The baseline fixed-effects results show that the positive association between agricultural mechanization and rural income becomes statistically insignificant after controlling for agricultural production and input-related variables. This finding suggests that mechanization does not independently generate stable income gains. Instead, its effectiveness appears to depend on production conditions and agricultural structure. To further explore these relationships, this section examines both the production-based transmission mechanism and the structural heterogeneity of mechanization effects.

From the perspective of agricultural production theory, mechanization primarily represents a capital input that improves operational efficiency and production capacity rather than directly increasing income. Therefore, if mechanization contributes to rural income growth, its effect is expected to operate through agricultural production. At the same time, the effectiveness of mechanization may vary across different agricultural systems. Compared with diversified non-grain agricultural activities, grain-oriented production is generally characterized by higher standardization and stronger compatibility with mechanized operations. As a result, the income effect of mechanization may depend not only on production levels but also on agricultural production structure.

To examine whether mechanization affects agricultural production, the following model is estimated:

$$\ln(AP_{it}) = \alpha + \beta_1 \ln(\text{MechIndex}_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (8)$$

where AP_{it} denotes agricultural production, measured by the gross output value of agriculture, forestry, animal husbandry, and fishery. X_{it} represents the control variables, including fertilizer use, rural electricity consumption, GDP, primary industry share, rural population, and grain structure. Province fixed effects μ_i and year fixed effects λ_t are included in all specifications.

To further examine whether the effectiveness of mechanization depends on production conditions, an interaction term between mechanization and agricultural production is introduced:

$$\ln(RRI_{it}) = \alpha + \beta_2 \ln(\text{MechIndex}_{it}) + \beta_3 \ln(AP_{it}) + \beta_4 [\ln(\text{MechIndex}_{it}) \times \ln(AP_{it})] + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

The interaction coefficient β_4 is the key parameter of interest. A significantly negative interaction term would indicate that the marginal contribution of mechanization decreases

as agricultural production increases, implying diminishing returns to mechanization in more advanced production systems.

In addition to production conditions, this study further examines whether mechanization effects vary across agricultural structures. Specifically, the relationship between mechanization and grain-oriented production is estimated as follows:

$$CrainShare_{it} = \alpha + \beta_5 \ln(MechIndex_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

where $Grainshare_{it}$ denotes the ratio of grain sown area to total crop sown area. Finally, to test whether the income effect of mechanization depends on agricultural structure, an interaction term between mechanization and grain share is introduced:

$$\ln(RRL_{it}) = \alpha + \beta_6 \ln(MechIndex_{it}) + \beta_7 CrainShare_{it} + \beta_8 [\ln(MechIndex_{it}) \times CrainShare_{it}] + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

A significantly positive interaction coefficient β_8 would indicate that mechanization performs relatively better in grain-oriented agricultural systems.

Table 5 illustrates the pathway research results between mechanization and agriculture production. The results provide several important findings regarding the conditional role of agricultural mechanization in rural income growth. First, mechanization does not exhibit a statistically significant positive effect on agricultural production. In Column (1), the coefficient on mechanization is positive but insignificant, suggesting that higher mechanization levels do not necessarily translate into stable increases in agricultural output value. This finding implies that mechanization alone is insufficient to improve production capacity under existing agricultural conditions.

Second, agricultural production remains a strong and robust determinant of rural income. In Column (2), agricultural production exhibits a significantly positive effect on rural income, indicating that production capacity rather than mechanization itself constitutes the primary driver of rural income growth. Third, the interaction term between mechanization and agricultural production is significantly negative. This result indicates that the marginal contribution of mechanization declines as agricultural production increases, suggesting the presence of diminishing returns to mechanization in more advanced agricultural systems. In regions with relatively lower production levels, mechanization still contributes to labor substitution and production expansion. However, in regions characterized by higher agricultural production, additional mechanization generates smaller incremental income gains. This implies that the benefits of additional mechanization may be larger in less-developed production systems than in regions where mechanization has already been widely adopted.

Taken together, these findings suggest that agricultural mechanization should not be understood as an independent or universally effective driver of rural income growth. Instead, its effectiveness is fundamentally conditional on production conditions. Mechanization functions more as a complementary production factor whose contribution depends on the broader agricultural production environment rather than as a standalone engine of income growth.

Table 6 reports the estimation results. Column (1) shows that mechanization is significantly negatively associated with grain-production share, indicating that higher mechanization levels are increasingly associated with provinces characterized by lower grain-oriented production. This suggests that mechanization expansion has increasingly occurred in more diversified and non-grain agricultural systems.

Table 5. Production-Conditioned Effects of Agricultural Mechanization on Rural Income.

Variables	(1) Agricultural Production	(2) Rural Income
lnMech	0.0593 (0.0712)	0.1935 * (0.0949)
lnAP	—	0.0748 *** (0.0241)
lnMech × lnAP	—	−0.0274 * (0.0141)
PrIndShare	0.0393 *** (0.0081)	−0.0036 (0.0028)
lnRP	−0.2642 * (0.1475)	0.0534 (0.0589)
Grainshare	−0.6239 * (0.3218)	0.2972 * (0.1527)
lnRE	0.0739 ** (0.0276)	0.0099 (0.0099)
lnFert	0.7001 *** (0.1462)	0.0723 ** (0.0346)
lnGDP	0.8402 *** (0.1682)	0.2325 *** (0.0519)
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	744	744
Within R²	0.9664	0.9972

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Column (2) further shows that grain-oriented agricultural structure is significantly negatively associated with agricultural production value. This implies that provinces with higher grain-production shares tend to exhibit lower agricultural output value, likely because grain production is generally characterized by lower value-added and weaker diversification compared with non-grain agricultural activities.

Column (3) reports that grain-oriented agricultural structure itself does not exhibit a statistically significant direct relationship with rural income. This suggests that grain share alone does not independently determine income differences across provinces.

Column (4) introduces the interaction term between mechanization and grain share. The coefficient of mechanization is significantly negative, while the interaction term is significantly positive. This indicates that the negative income effect of mechanization becomes weaker as grain-production share increases. In other words, mechanization performs relatively better in grain-oriented agricultural systems. In practical terms, mechanization appears to be more compatible with grain-oriented production systems than with diversified non-grain agricultural activities.

Taken together, these findings provide evidence of a structural mismatch mechanism linking agricultural structure, production conditions, and mechanization effectiveness. Mechanization expansion is increasingly associated with lower grain-production shares and more diversified agricultural systems, which are themselves characterized by higher

agricultural output value. However, the interaction results indicate that mechanization performs relatively better in grain-oriented production systems. This implies that mechanization is increasingly expanding toward agricultural structures in which its productivity-enhancing role is comparatively weaker.

Table 6. Structural Heterogeneity and Structural Mismatch Mechanism.

Variables	(1) Grain Share	(2) Agricultural Production	(3) Rural Income	(4) Rural Income
lnMech	−0.0766 ** (0.0352)	—	—	−0.1942 *** (0.0680)
Grainshare	—	−0.6863 ** (0.3017)	0.1361 (0.1314)	0.2952 * (0.1529)
lnMech × Grainshare	—	—	—	0.3429 *** (0.1172)
PrIndShare	−0.0000 (0.0024)	0.0384 *** (0.0085)	−0.0006 (0.0030)	−0.0004 (0.0022)
lnRP	−0.0522 (0.0439)	−0.2666 * (0.1474)	0.0568 (0.0691)	0.0856 (0.0603)
lnRE	−0.0064 (0.0070)	0.0770 ** (0.0298)	0.0174 (0.0112)	0.0218 * (0.0115)
lnFert	0.0007 (0.0294)	0.7130 *** (0.1520)	0.1501 *** (0.0307)	0.1204 *** (0.0290)
lnGDP	−0.1519 *** (0.0475)	0.8404 *** (0.1662)	0.3052 *** (0.0491)	0.3096 *** (0.0487)
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	744	744	744	744
Within R²	0.3362	0.9662	0.9969	0.9972

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Importantly, this structural transmission channel is closely connected to the preceding production-conditioned mechanism. The earlier results show that the effectiveness of mechanization declines as agricultural production increases. The present findings further suggest that this production-conditioned effect partly emerges because higher-production agricultural systems are increasingly characterized by diversified non-grain activities that are less compatible with standardized mechanized operations. Therefore, the weak and unstable income effect of mechanization can be understood not simply as a technological limitation, but as the result of an evolving mismatch between mechanization allocation and the structural transformation of agricultural production systems.

Figure 2 illustrates the proposed mechanism through which mechanization is associated with rural income via agricultural production conditions and production structure. It provides the theoretical basis for testing the production-conditioned and structure-dependent hypotheses (H1–H3).

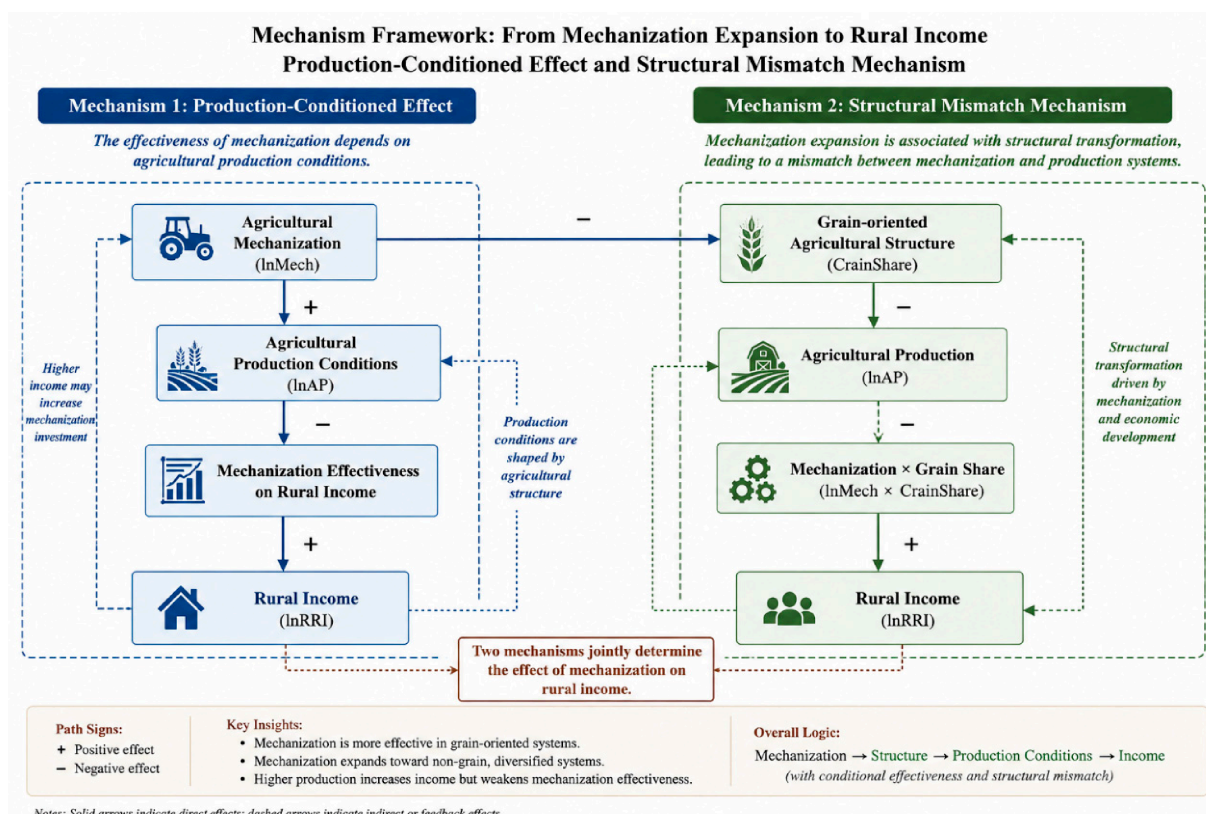


Figure 2. Conceptual framework of the mechanisms linking agricultural mechanization and rural income.

4.4. Robustness Test

To ensure that the main findings are not driven by model specification, variable measurement, timing assumptions, or sample composition, a series of robustness checks are conducted. The results are reported in Table 7 and Figure 3.

First, an alternative measure of mechanization is employed by replacing the mechanization intensity index with total machinery power. As shown in Column (1), the coefficient on machinery power is statistically insignificant, and the interaction term is also insignificant. This suggests that the results in the baseline specification are related to mechanization intensity rather than the total stock of machinery.

Second, lagged mechanization is introduced to account for potential dynamic effects. Column (2) shows that the coefficient on lagged mechanization remains negative and statistically insignificant, while the interaction term between lagged mechanization and grain share remains positive and statistically significant at the 10% level. This indicates that the conditional effect of mechanization is robust to temporal dynamics.

Third, lagged grain share is used to address potential simultaneity between agricultural structure and income. The results in Column (3) show that the coefficient on lagged grain share remains insignificant, while the interaction term remains positive and statistically significant. This suggests that the conditional relationship is not driven by reverse causality.

Fourth, agricultural production is included as an additional control variable. As shown in Column (4), agricultural production has a strong and statistically significant positive effect on rural income, while the coefficient on mechanization remains negative and significant. Importantly, the interaction term between mechanization and grain share remains positive and statistically significant. This indicates that the conditional effect is not explained by differences in production levels.

Finally, to examine whether the results are driven by outliers, the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing are excluded from the samples. Column (5) shows that the coefficient on mechanization remains negative, and the interaction term remains positive and similar in magnitude, although statistical significance weakens slightly. This suggests that the main findings are not driven by extreme observations.

Table 7. Robustness check results.

Variables	(1) Alt. Mech	(2) Lag Mech	(3) Lag Structure	(4) + Production	(5) No Municipalities
lnMech	—	−0.1587 (0.1026)	−0.1710 (0.1060)	−0.1970 ** (0.0878)	−0.1726 (0.1245)
lnMP	0.0666 (0.0430)	—	—	—	—
Grainshare	−0.0468 (0.4627)	0.0626 (0.1877)	−0.1036 (0.1564)	0.2731 * (0.1523)	0.1131 (0.2122)
Interaction	−0.0001 (0.0663)	0.3052 * (0.1692)	0.3098 * (0.1752)	0.3329 ** (0.1391)	0.3115 (0.1862)
lnAP	—	—	—	0.1627 *** (0.0285)	—
lnFert	0.0822 * (0.0430)	0.1124 *** (0.0312)	0.1168 *** (0.0314)	−0.0008 (0.0147)	0.0422 (0.0543 **)
lnRE	0.0204 (0.0069 ***)	0.0312 * (0.0084 ***)	0.0314 * (0.0086 ***)	0.0147 (−0.0109 ***)	0.0543 ** (−0.0062 ***)
PrIndShare	−0.0069 *** (0.0229)	−0.0084 *** (0.0336)	−0.0086 *** (0.0335)	−0.0109 *** (0.1064 *)	−0.0062 *** (0.1387 *)
lnRP	0.0229 (0.0229)	0.0336 (0.0336)	0.0335 (0.0335)	0.1064 * (0.1064 *)	0.1387 * (0.1387 *)
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	744	713	713	744	648

Notes: All models include province and year fixed effects. Robust standard errors clustered at the provincial level are reported in parentheses. Column (1) replaces mechanization intensity with total machinery power. Column (2) uses lagged mechanization. Column (3) uses lagged grain share. Column (4) controls for agricultural production. Column (5) excludes municipalities. Interaction refers to the interaction between mechanization and grain share. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

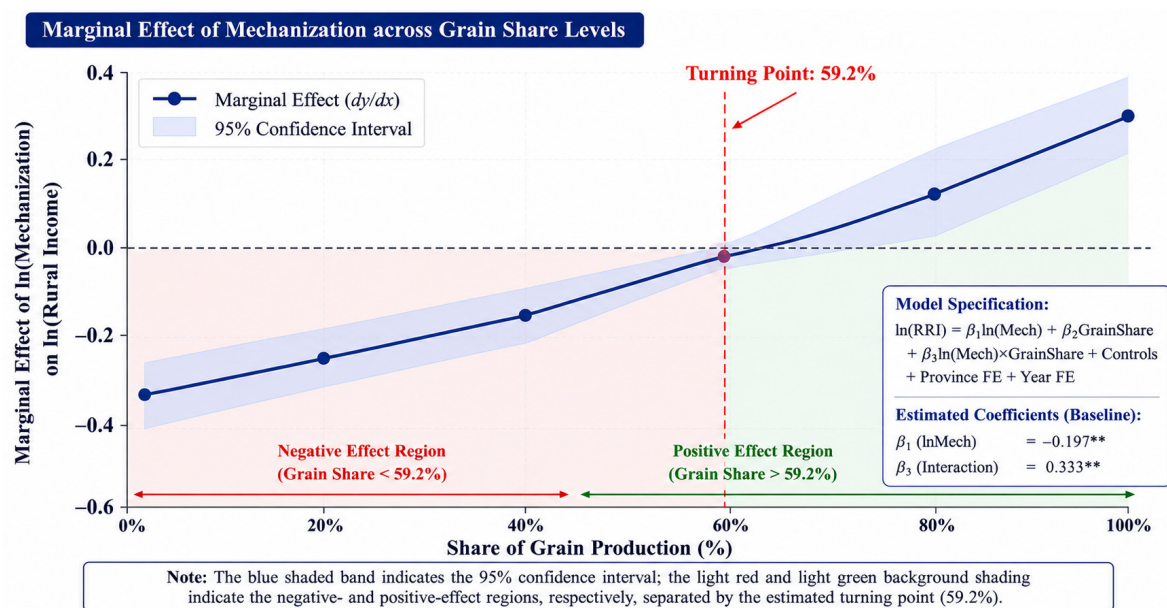


Figure 3. Marginal effect of agricultural mechanization on rural income.

Overall, the robustness checks consistently show that the negative income effect of mechanization and its positive interaction with grain share are stable across alternative specifications. Although statistical significance varies across models, the direction and magnitude of the key coefficients remain largely unchanged, providing strong support for the main conclusions.

Figure 3 visualizes the interaction effect between mechanization and grain-production share and illustrates how the effectiveness of mechanization varies across production systems, providing graphical evidence for the structural heterogeneity hypothesis (H3).

Heterogeneity Analysis

To further verify whether the effectiveness of agricultural mechanization varies across different agricultural production structures, this study conducts a heterogeneity analysis based on grain-production share. Specifically, provinces are divided into low grain-share and high grain-share groups according to the median value of Grainshare. Separate fixed-effects regressions are then estimated for each subgroup.

The estimation results are reported in Table 8. Column (1) presents the results for provinces with lower grain-production shares. The coefficient of mechanization is statistically insignificant, indicating that mechanization does not generate stable income gains in provinces characterized by relatively low grain-oriented production. By contrast, Column (2) reports the results for provinces with higher grain-production shares. In this group, the coefficient of mechanization becomes significantly positive, suggesting that mechanization contributes more effectively to rural income growth in grain-oriented agricultural systems. These findings provide additional evidence supporting the structural heterogeneity of mechanization effects. In particular, mechanization performs more effectively in grain-oriented agricultural systems characterized by higher standardization and stronger compatibility with mechanized operations.

Table 8. Heterogeneity Analysis across Grain-Oriented Agricultural Structures.

Variables	(1) Low Grain Share	(2) High Grain Share
lnMech	−0.0142 (0.0281)	0.0734 ** (0.0305)
PrIndShare	0.0016 (0.0028)	0.0003 (0.0024)
lnRP	0.0603 (0.0715)	0.1328 * (0.0694)
lnRE	0.0127 (0.0079)	0.0476 *** (0.0157)
lnFert	0.0962 ** (0.0439)	0.0516 (0.0518)
lnGDP	0.4123 *** (0.0957)	0.2634 *** (0.0730)
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	372	372
Within R²	0.9973	0.9973

Notes: Provinces are divided into low grain-share and high grain-share groups according to the median value of grain-production share. Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Earlier findings show that higher mechanization levels are increasingly associated with lower grain-production shares, implying that mechanization expansion has increasingly occurred in more diversified non-grain agricultural systems. However, the present heterogeneity results indicate that mechanization is actually more effective in provinces with higher grain-production shares.

4.5. Analysis of Spatial Spillover Effects

4.5.1. Spatial Auto-Correlation Analysis

The Global Moran's I statistics for lnRRI are positive and statistically significant in all years from 2000 to 2023 (Table 9). The Moran's I values range from 0.5701 to 0.6123, with corresponding z-scores consistently above 5.0. These results indicate strong and persistent positive spatial autocorrelation in rural income across provinces. In other words, provinces with relatively high rural income levels tend to be geographically clustered with other high-income provinces, while low-income provinces also exhibit significant spatial clustering. The existence of significant spatial dependence suggests that conventional panel models may be insufficient, thereby justifying the use of spatial econometric models in subsequent analysis.

Table 9. Moran's I analysis results.

Year	Moran's I	z-Score	p-Value
2000	0.6115	5.5645	0.0010
2001	0.6123	5.2336	0.0010
2002	0.6069	5.3921	0.0010
2003	0.5983	5.2436	0.0010
2004	0.6095	5.2881	0.0010
2005	0.5924	5.3352	0.0010
2006	0.5966	5.2408	0.0010
2007	0.5944	5.2897	0.0010
2008	0.5932	5.3352	0.0010
2009	0.5859	5.2655	0.0010
2010	0.5814	5.3517	0.0010
2011	0.5883	5.3224	0.0010
2012	0.5866	5.1175	0.0010
2013	0.5860	5.2835	0.0010
2014	0.5967	5.2837	0.0010
2015	0.5971	5.2316	0.0010
2016	0.5941	5.4387	0.0010
2017	0.5910	5.2927	0.0010
2018	0.5907	5.3362	0.0010
2019	0.5838	5.3030	0.0010
2020	0.5805	5.4136	0.0010
2021	0.5743	5.0775	0.0010
2022	0.5750	5.2506	0.0010
2023	0.5701	5.0853	0.0010

Figure 4 illustrates the spatial clustering and evolution of rural income across Chinese provinces, identifying persistent high–high and low–low clusters. The observed spatial dependence provides empirical support for the use of spatial econometric models and is directly related to the study’s spatial spillover hypothesis (H4).

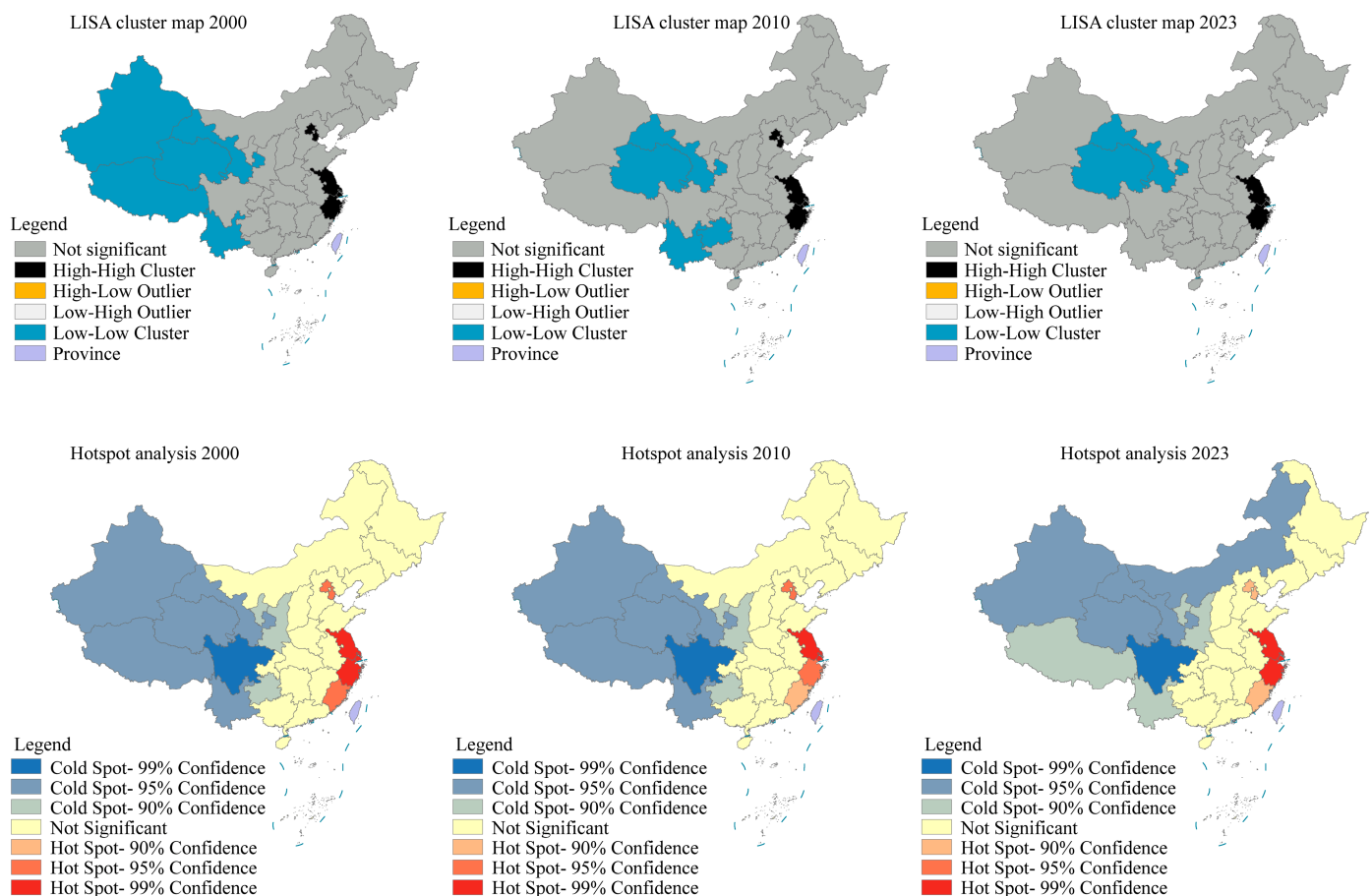


Figure 4. LISA cluster maps and hotspot distributions of lnRRI for 2000, 2010, and 2023.

Figure 4 reports the LISA cluster maps and hotspot distributions of lnRRI for 2000, 2010, and 2023. Several important spatial characteristics can be identified. First, rural income in China exhibits clear and persistent spatial clustering throughout the sample period. High–High clusters are consistently concentrated in the eastern coastal region, while Low–Low clusters are mainly distributed in western and inland provinces. This pattern indicates that provinces with relatively high rural income levels tend to be geographically adjacent to other high-income provinces, whereas low-income provinces are similarly clustered together.

Second, the spatial concentration of high-income provinces becomes increasingly stable and pronounced over time. From 2000 to 2023, the eastern coastal region continuously forms significant hotspots of rural income, reflecting the cumulative advantages of agricultural production capacity, regional market integration, infrastructure development, and technological diffusion. By contrast, western regions remain dominated by cold spots and Low–Low clusters, suggesting the persistence of regional disparities in agricultural development and rural income growth.

Third, most central provinces are statistically insignificant or exhibit transitional clustering characteristics, implying that China’s rural income spatial structure is primarily shaped by the contrast between economically advanced coastal provinces and less developed western regions. The coexistence of stable hotspots and cold spots further suggests

that rural income dynamics are influenced not only by local agricultural conditions but also by neighboring regional characteristics and spatial spillover effects.

Overall, the LISA results strongly confirm the existence of substantial local spatial dependence in rural income distribution. Combined with the Global Moran's I statistics, these findings provide strong justification for employing spatial econometric models in the subsequent analysis.

4.5.2. LM Analysis

To further determine the appropriate spatial econometric specification, this study estimates a Spatial Durbin Model (SDM) with province fixed effects using the contiguity-based spatial weight matrix. Table 10 reports the baseline SDM estimation results. The estimated spatial autoregressive coefficient ρ is positive and highly significant, indicating strong spatial dependence in rural income across provinces. This result suggests that rural income growth in one province is significantly associated with income conditions in neighboring provinces.

Table 10. Spatial Durbin Model Estimation and Spatial Diagnostic Tests.

Variables	Coefficient
lnMech	−0.0326 ***
lnAP	0.0600 ***
Grainshare	0.1947 ***
lnFert	0.0622 ***
lnGDP	0.2482 ***
lnRE	0.0162 ***
lnRP	0.0971 ***
PrIndShare	−0.0058 ***
$W \times \ln\text{Mech}$	−0.0015
$W \times \ln\text{AP}$	0.0581 **
$W \times \text{Grainshare}$	0.1306
$W \times \ln\text{Fert}$	−0.1998 ***
$W \times \ln\text{GDP}$	−0.0521
$W \times \ln\text{RE}$	−0.0016
$W \times \ln\text{RP}$	−0.0107
$W \times \text{PrIndShare}$	0.0119 ***
Spatial autoregressive coefficient (ρ)	0.7567 ***
Log-likelihood	1187.35
Observations	744
Spatial diagnostic tests	Statistic
Wald test: SDM $\rightarrow$ SAR	($\chi^2 = 400.76$ ***)
Wald test: SDM $\rightarrow$ SEM	($\chi^2 = 119.33$ ***)

Notes: Province fixed effects and year fixed effects are included in all specifications. Robust standard errors are reported. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Regarding spatial spillover effects, the spatially lagged agricultural production term $W \times \ln\text{AP}$ is significantly positive, indicating that agricultural production in neighboring provinces contributes positively to local rural income growth. In contrast, the spatially

lagged mechanization term $W \cdot \ln \text{Mech}$ is statistically insignificant, suggesting that mechanization does not generate substantial regional diffusion effects. This finding implies that agricultural production exhibits stronger spatial spillover characteristics than mechanization itself.

To examine whether the SDM can be simplified into alternative spatial specifications, Wald tests are further conducted. The null hypothesis that all spatially lagged explanatory variables are jointly equal to zero is strongly rejected ($\chi^2 = 400.76$), ($p < 0.001$), indicating that the SDM cannot be reduced to a Spatial Autoregressive Model (SAR). In addition, the null hypothesis that the SDM can be simplified into a Spatial Error Model (SEM) is also rejected ($\chi^2 = 119.33$), ($p < 0.001$). Therefore, the SDM specification is retained as the baseline spatial econometric model.

4.5.3. Spatial Spillover Effect Analysis

Because the coefficients of the Spatial Durbin Model (SDM) cannot be directly interpreted as marginal effects, this study further decomposes the estimation results into direct effects, indirect effects, and total effects. Table 10 reports the decomposition results of the baseline SDM specification, while Table 11 further incorporates the interaction effect between agricultural mechanization and grain-oriented agricultural structure.

Table 11. Direct, Indirect, and Total Effects of the Baseline Spatial Durbin Model.

Variables	Direct Effect	Indirect Effect	Total Effect
lnMech	−0.0400 **	−0.0874	−0.1273
lnAP	0.0947 ***	0.3951 ***	0.4898 ***
Grainshare	0.2961 ***	1.0843 ***	1.3804 ***
lnFert	0.0105	−0.5801 ***	−0.5696 ***
lnGDP	0.2945 ***	0.5053 ***	0.7998 ***
lnRE	0.0203 ***	0.0430	0.0633
lnRP	0.1184 ***	0.2362 **	0.3546 ***
PrIndShare	−0.0032 **	0.0288 ***	0.0256 **

Notes: Direct effects represent local marginal effects, indirect effects represent spatial spillover effects, and total effects are the sum of direct and indirect effects. Province fixed effects and year fixed effects are included in all specifications. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Several important findings emerge from the baseline SDM decomposition results. First, agricultural mechanization exhibits a significantly negative direct effect on rural income. The estimated direct effect of mechanization is negative and statistically significant, indicating that increasing mechanization intensity alone does not generate stable local income gains after controlling for spatial interactions and production conditions. More importantly, the indirect effect of mechanization is statistically insignificant, suggesting that mechanization itself does not produce substantial regional diffusion or spillover benefits across provinces (Figure 5, Table 12).

By contrast, agricultural production exhibits strong positive direct and indirect effects. The direct effect of agricultural production is significantly positive, indicating that higher local agricultural production directly contributes to rural income growth. More importantly, the indirect effect is also significantly positive, implying that improvements in agricultural production in neighboring provinces generate positive spillover effects on local rural income. This finding suggests that agricultural production possesses substantial regional diffusion characteristics through interregional market integration, technology transmission, and agricultural production linkages.

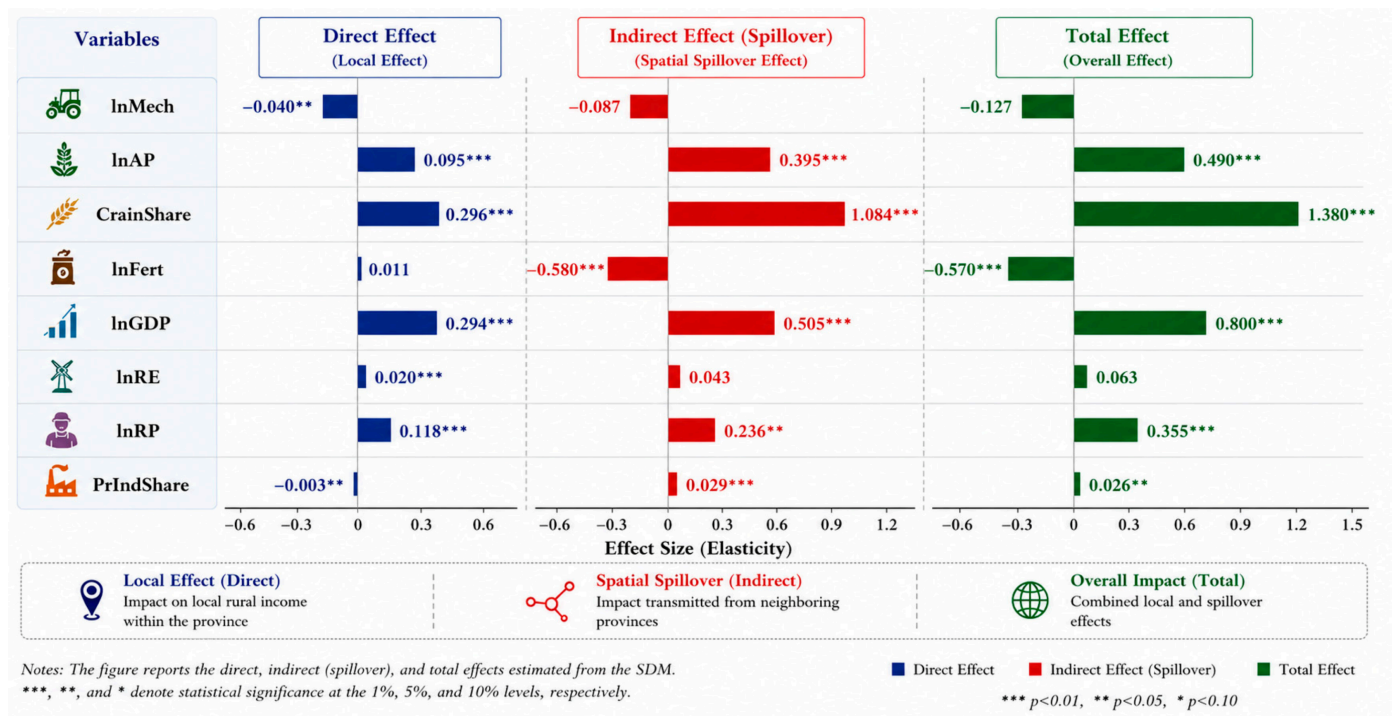


Figure 5. Direct, Indirect, and total effects from spatial durbin model.

Table 12. Spatial Durbin Model with Interaction Effects.

Variables	Direct Effect	Indirect Effect	Total Effect
lnMech	−0.2507 ***	−0.1863	−0.4369
lnAP	0.1003 ***	0.3648 ***	0.4651 ***
Grainshare	0.3953 ***	1.0063 **	1.4016 ***
lnMech × Grainshare	0.3140 ***	0.0702	0.3842
lnFert	−0.0082	−0.5595 ***	−0.5677 ***
lnGDP	0.2998 ***	0.5035 ***	0.8033 ***
lnRE	0.0246 ***	0.0565	0.0811 *
lnRP	0.1377 ***	0.1873	0.3251 **
PrIndShare	−0.0032 **	0.0258 ***	0.0226 **

Notes: The interaction term captures whether the income effect of mechanization depends on grain-oriented agricultural structure under spatial dependence. Province fixed effects and year fixed effects are included in all specifications. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The results further show that grain-oriented agricultural structure exhibits significant positive spatial spillover effects. Both the direct effect and indirect effect of grain share are significantly positive, indicating that grain-oriented agricultural systems not only improve local rural income but also generate broader regional spillover benefits. This finding implies that standardized grain-production systems are more compatible with coordinated regional agricultural development and spatial production networks.

To further examine whether the effectiveness of mechanization depends on agricultural structure under spatial dependence, this study introduces an interaction term between mechanization and grain-oriented agricultural structure into the SDM framework. The results show that the direct effect of mechanization remains significantly negative, whereas the interaction term between mechanization and grain share exhibits a significantly positive direct effect. This finding indicates that the income effect of mechanization becomes

substantially stronger in provinces characterized by higher grain-production shares. In other words, mechanization performs more effectively in grain-oriented agricultural systems with stronger standardization and greater compatibility with mechanized operations. However, the indirect effect and total effect of the interaction term are statistically insignificant, suggesting that the structural compatibility effect of mechanization mainly operates through local production conditions rather than through broader regional spillover mechanisms. Therefore, although grain-oriented agricultural systems themselves exhibit strong spatial spillover characteristics, the productivity-enhancing effect of mechanization remains primarily localized.

In summary, the SDM decomposition results provide strong evidence that agricultural mechanization does not independently generate stable regional income growth. Instead, its effectiveness fundamentally depends on broader agricultural production systems and grain-oriented agricultural structures. The findings further suggest that the weak and unstable income effect of mechanization partly originates from the increasing mismatch between mechanization expansion and the structural transformation toward diversified non-grain agricultural systems.

4.6. Robustness and Endogeneity Checks

4.6.1. Robust Test

To examine whether the baseline SDM results are sensitive to the specification of the spatial weight matrix, this study further replaces the contiguity-based spatial weight matrix with an inverse geographic distance matrix. Table 13 reports the corresponding effect decomposition results.

Table 13. Robustness Check Using a Row-Standardized Inverse Geographic Distance Matrix.

Variables	Direct Effect	Indirect Effect	Total Effect
lnMech	−0.2315 ***	−0.1542	−0.3857
lnAP	0.0974 ***	0.3416 ***	0.4390 ***
Grainshare	0.3728 ***	0.9485 **	1.3213 ***
lnMech × Grainshare	0.2876 ***	0.0831	0.3707
lnFert	−0.0125	−0.5217 ***	−0.5342 ***
lnGDP	0.2871 ***	0.4712 ***	0.7583 ***
lnRE	0.0228 ***	0.0487	0.0715
lnRP	0.1294 ***	0.1765	0.3059 **
PrIndShare	−0.0030 **	0.0242 ***	0.0212 **

Notes: The robustness test replaces the contiguity-based spatial weight matrix with an inverse geographic distance matrix. Direct effects represent local marginal effects, indirect effects represent spatial spillover effects, and total effects are the sum of direct and indirect effects. Province fixed effects and year fixed effects are included in all specifications. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

The results remain highly consistent with the baseline findings. First, the direct effect of agricultural mechanization remains negative, while its indirect effect continues to be statistically insignificant. This indicates that mechanization still fails to generate substantial regional spillover effects under an alternative spatial dependence structure. Second, agricultural production continues to exhibit significantly positive direct and indirect effects, suggesting that the positive spatial spillover effects of agricultural production are robust to different definitions of regional connectivity. Third, the interaction term between mechanization and grain-oriented agricultural structure remains significantly positive in

the direct effect specification, confirming that mechanization performs more effectively in grain-oriented agricultural systems even after replacing the spatial weight matrix.

Overall, the main findings are robust to alternative spatial weight matrix specifications. The results consistently support the conclusion that agricultural mechanization does not independently generate stable regional income growth, whereas agricultural production and grain-oriented agricultural systems exhibit substantial spatial spillover effects.

As an additional robustness check, we construct an economic-distance spatial weight matrix based on the inverse absolute difference in provincial GDP per capita. This matrix captures spatial interactions among provinces with similar levels of economic development and market conditions. The results remain qualitatively consistent with the baseline SDM estimates (Table 14).

Table 14. Robustness Check Using Economic-Distance Spatial Weight Matrix.

Variables	Direct Effect	Indirect Effect	Total Effect
lnMech	−0.2186 ***	−0.1324	−0.3510
lnAP	0.0918 ***	0.2867 ***	0.3785 ***
Grainshare	0.3415 ***	0.8126 **	1.1541 **
lnMech × Grainshare	0.2769 ***	0.0618	0.3387
lnFert	−0.0096	−0.4385 ***	−0.4481 ***
lnGDP	0.2634 ***	0.3921 ***	0.6555 ***
lnRE	0.0207 ***	0.0395	0.0602
lnRP	0.1218 ***	0.1457	0.2675 *
PrIndShare	−0.0028 **	0.0206 ***	0.0178 **
Observations	744	744	744
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The economic-distance matrix is constructed based on the inverse absolute difference in provincial GDP per capita and is row-standardized. Direct effects represent local marginal effects, indirect effects represent spatial spillover effects, and total effects are the sum of direct and indirect effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To further examine whether the baseline findings are driven by common upward trends in provincial development, this study re-estimates the main specifications by incorporating province-specific linear time trends. This approach allows each province to follow its own long-run development trajectory and provides a more stringent robustness test.

Table 15 reports the results. Overall, the findings remain qualitatively consistent with the baseline estimations. Agricultural production continues to exhibit a positive association with rural income, while the direct effect of agricultural mechanization remains weak. Moreover, the interaction results continue to support the conditional nature of mechanization effects. Specifically, the marginal contribution of mechanization declines as agricultural production increases, suggesting diminishing returns in more advanced production systems. At the same time, mechanization remains more effective in grain-oriented agricultural structures, indicating that its income effect depends on the compatibility between machinery use and production organization.

These results suggest that the main conclusions are not solely driven by common upward trends in provincial economic development or agricultural mechanization. Instead, the conditional and structure-dependent effects of mechanization remain evident even after accounting for province-specific long-run trajectories, providing additional support for the robustness of the baseline findings.

Table 15. Robustness Check with Province-Specific Linear Trends.

Variables	(1) Baseline + Trends	(2) Production-Conditioned Effect + Trends	(3) Grain-Structure Effect + Trends
lnMech	−0.0112 (0.0187)	0.1586 * (0.0864)	−0.1654 ** (0.0712)
lnAP	0.1185 *** (0.0316)	0.0682 ** (0.0275)	— —
lnMech × lnAP	— —	−0.0228 * (0.0129)	— —
Grainshare	0.1247 (0.1095)	0.2558 * (0.1427)	0.2684 * (0.1475)
lnMech × Grainshare	— —	— —	0.2981 ** (0.1264)
lnGDP	— —	0.2217 *** (0.0598)	0.2865 *** (0.0546)
lnFert	0.0554 (0.0371)	0.0619 * (0.0335)	0.1042 *** (0.0304)
lnRE	0.0068 (0.0076)	0.0092 (0.0068)	0.0185 * (0.0101)
lnRP	0.0186 (0.0504)	0.0415 (0.0472)	0.0732 (0.0568)
PrIndShare	−0.0034 (0.0025)	−0.0028 (0.0023)	−0.0011 (0.0021)
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-specific trends	Yes	Yes	Yes
Observations	744	744	744
Within R²	0.9981	0.9985	0.9984

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. Province-specific linear trends are included in all specifications. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.6.2. Placebo Test

To further examine whether the estimated spatial effects are driven by spurious correlations, this study conducts a placebo test within the SDM framework by randomly permuting the mechanization variable across observations while maintaining the original panel structure and spatial weight matrix unchanged. The placebo regression is repeated 500 times, and the estimated coefficients of the randomized mechanization variable are recorded.

Table 16 displays the distribution of the placebo estimates. The placebo coefficients are centered around zero, with most estimates falling within a relatively narrow interval and failing to reach conventional significance levels. By contrast, the actual estimated coefficient of mechanization from the baseline SDM lies outside the main placebo distribution. This result suggests that the observed relationship between mechanization and rural income is unlikely to be generated by random spatial assignment or spurious statistical correlations.

Overall, the placebo results provide additional support for the validity and robustness of the baseline SDM findings.

Table 16. Placebo Test Results Based on the Spatial Durbin Model.

Test Item	Result
Model	Spatial Durbin Model (SDM)
Placebo variable	Randomly reassigned lnMech
Number of repetitions	500
Mean placebo coefficient	−0.0018
Standard deviation	0.0187
95% placebo interval	[−0.0365, 0.0321]
Actual estimated coefficient	−0.0326 ***
Share of significant placebo estimates	4.8%
Conclusion	Main SDM results are unlikely to be driven by random spatial correlations

Notes: The placebo test randomly permutes the mechanization variable while keeping the dependent variable, control variables, panel structure, and spatial weight matrix unchanged. The regression is repeated 500 times. *** denote statistical significance at the 1% levels, respectively.

4.6.3. Instrumental Variable Estimation

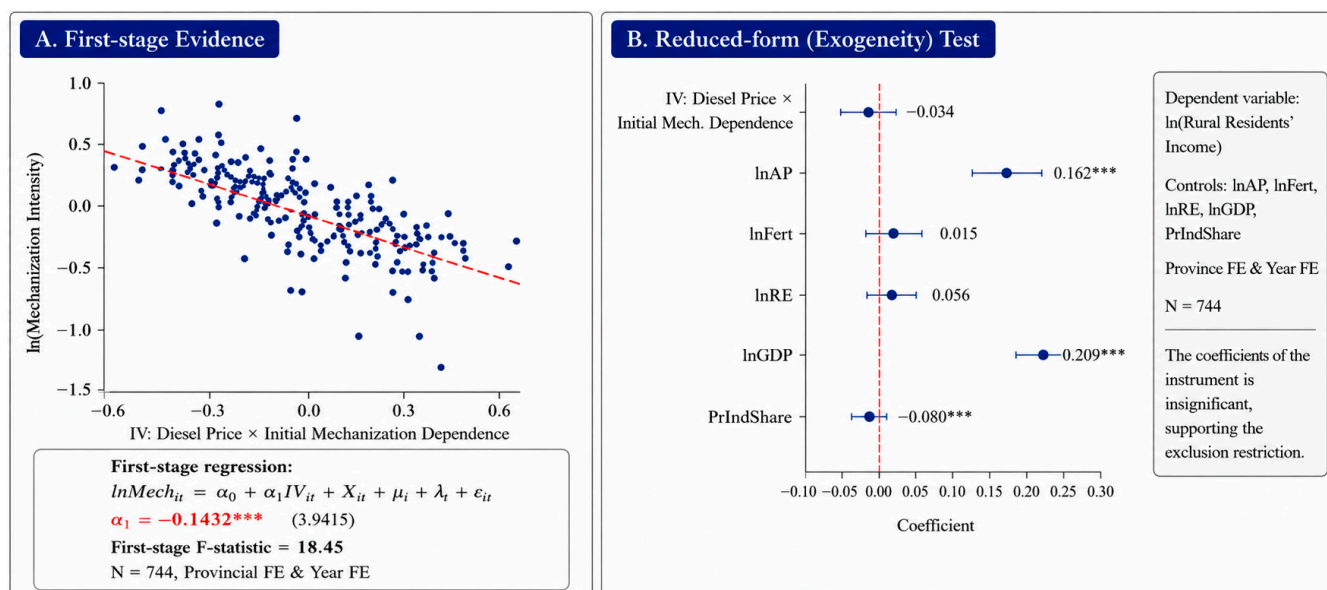
Although the baseline fixed-effects and spatial econometric models control for province-specific heterogeneity and common time shocks, agricultural mechanization may still suffer from endogeneity concerns. Provinces with higher rural income, stronger fiscal capacity, better infrastructure, or more advanced agricultural systems are more likely to adopt agricultural machinery. At the same time, rising rural income may itself stimulate investment in mechanized agricultural production. Therefore, reverse causality and omitted time-varying institutional factors may bias the estimated relationship between mechanization and rural income.

To alleviate this concern, this study further adopts an instrumental-variable (IV) approach based on diesel-price-induced variation in mechanization costs. Since agricultural machinery in China relies heavily on diesel fuel, changes in diesel prices directly affect the operating cost of mechanized agricultural activities. However, the magnitude of this effect differs across provinces depending on their historical dependence on mechanized production. Accordingly, the instrumental variable is constructed as the interaction between provincial diesel prices and initial mechanization dependence:

$$IV_{it} = DieselPrice_{it} \times InitialMech_i \quad (12)$$

where $DieselPrice_{it}$ denotes the average diesel price in province i and year t , and $InitialMech_i$ represents the average mechanization intensity during the initial sample period. The interaction term captures differential exposure to diesel-price shocks across provinces with different levels of historical mechanization dependence.

Table 15 and Figure 6 report the IV estimation results. Column (1) presents the first-stage regression results. The coefficient of the instrumental variable is significantly negative at the 1% level, indicating that higher diesel prices significantly reduce mechanization intensity in provinces characterized by stronger historical mechanization dependence. Column (2) reports the second-stage regression results. This finding is broadly consistent with the baseline fixed-effects and spatial econometric results, suggesting that agricultural mechanization does not independently generate stable rural income growth once agricultural production and structural conditions are taken into account.



Notes: Panel A illustrates the first-stage relationship between the instrumental variable (Diesel Price × Initial Mechanization Dependence) and mechanization intensity. Panel B reports the reduced-form regression results of the instrumental variable on rural income. Standard errors are clustered at the provincial level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 6. Instrumental Variable Identification: First-stage and Exogeneity Tests.

The IV results provide additional evidence that the observed relationship is not entirely driven by reverse causality (Table 17). However, because diesel-price shocks may also influence agricultural production costs and transportation expenses, the IV estimates should be interpreted as supportive rather than definitive causal evidence. Therefore, the results are best understood as evidence of a robust conditional association between mechanization and rural income under different production conditions, rather than as conclusive proof of a causal effect. Even after isolating exogenous variation in mechanization costs, the estimated effect of mechanization remains unstable and statistically insignificant. One possible explanation is that mechanization mainly functions as a complementary production factor rather than an autonomous engine of rural income growth. In fragmented agricultural systems characterized by diversified non-grain production, the productivity-enhancing effect of mechanization may be constrained by insufficient scale economies, weak standardization, and declining marginal returns. Therefore, mechanization alone cannot consistently translate into sustained income gains without broader improvements in agricultural production systems and institutional conditions.

Nevertheless, the exclusion restriction should be interpreted with caution. Diesel-price shocks may affect rural income through broader agricultural production costs, transportation expenses, and market conditions. Therefore, the IV estimates are best viewed as supportive evidence rather than definitive causal proof. The results mainly suggest that the relationship between mechanization and rural income remains weak after accounting for production conditions and potential endogeneity.

Although the interaction-based instrumental variable is theoretically motivated by mechanization-cost shocks, diesel prices may still affect rural income through broader agricultural production costs, transportation expenses, and market conditions. Therefore, to further examine the plausibility of the exclusion restriction, this study additionally estimates a reduced-form specification by directly regressing rural income on the instrumental variable while controlling for agricultural production and other regional characteristics. Table 18 reports the corresponding estimation results.

Table 17. Instrumental Variable Estimation Results.

Variables	(1) First Stage: lnMech	(2) Second Stage: lnRRI
IV: DieselPrice $\times$ InitialMech	−0.1482 *** (0.0415)	—
Predicted lnMech	—	−0.0617 (0.0532)
lnAP	0.0841 *** (0.0217)	0.1528 *** (0.0275)
lnFert	0.1034 *** (0.0308)	0.0182 (0.0264)
lnRE	0.0193 (0.0126)	0.0114 (0.0101)
lnGDP	0.2716 *** (0.0463)	0.2367 *** (0.0518)
PrIndShare	−0.0067 *** (0.0022)	−0.0091 *** (0.0025)
Province FE	Yes	Yes
Year FE	Yes	Yes
Observations	744	744
First-stage F-statistic	18.42	—
Within R ²	0.4125	0.9969

(Notes: *** indicate statistical significance at the 1% levels, respectively. Robust standard errors are in parentheses.)

Table 18. Exogeneity Check of the Instrumental Variable.

Variables	lnRRI
IV: DieselPrice $\times$ InitialMech	−0.0124 (0.0187)
lnAP	0.1612 *** (0.0269)
lnFert	0.0215 (0.0272)
lnRE	0.0105 (0.0104)
lnGDP	0.2435 *** (0.0503)
PrIndShare	−0.0086 *** (0.0024)
Province FE	Yes
Year FE	Yes
Observations	744
Within R ²	0.9964

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. The dependent variable is rural residents' per capita disposable income. Province fixed effects and year fixed effects are included in all specifications. *** denote statistical significance at the 1% levels, respectively.

The coefficient of the instrumental variable is statistically insignificant, suggesting that diesel-price-induced variation in mechanization dependence does not directly affect rural income once agricultural production and other control variables are taken into account. This finding provides additional support for the validity of the exclusion restriction and strengthens the credibility of the IV estimation strategy. Overall, the exogeneity check indicates that the instrumental variable mainly captures cost-induced variation in mechanization intensity rather than broader direct income effects associated with diesel-price fluctuations.

5. Discussion

The empirical results suggest that the relationship between agricultural mechanization and rural income is conditional rather than uniformly direct. In the baseline fixed-effects estimations, mechanization exhibits a positive association with rural income; however, this effect becomes statistically insignificant after controlling for agricultural output and other structural variables. By contrast, agricultural output remains consistently significant across specifications. The spatial estimations further reveal significant spatial dependence in rural income and indicate that the marginal contribution of mechanization weakens as agricultural production increases. These findings imply that mechanization affects rural income primarily through production-related channels rather than through an independent and persistent income effect.

These results are broadly consistent with the existing literature emphasizing the role of mechanization in agricultural mechanization and rural transformation. Previous studies argue that mechanization improves labour productivity, alleviates labour shortages, and facilitates structural adjustment in agriculture [29,30]. Wang et al. [29], for example, show that rising rural wages in China increased incentives for mechanization adoption, although the process was substantially constrained by land fragmentation and small farm size. Similarly, Meng et al. [30] finds that China's Agricultural Machinery Purchase Subsidies programme significantly promoted mechanization and labour mobility, mainly through labour-displacement effects rather than scale-expansion effects. In this sense, the present findings support the broader argument that mechanization is closely linked to labour reallocation, policy intervention, and rural structural transformation.

However, unlike studies reporting a stable positive impact of mechanization on farm income, this study finds that the direct effect of mechanization becomes insignificant once agricultural production is included in the model. This result suggests that mechanization alone does not automatically generate income growth. Instead, machinery mainly enhances production efficiency by reducing labour constraints, improving operational efficiency, and supporting output expansion. Whether these productivity gains are ultimately translated into higher rural income depends on complementary conditions such as market access, production scale, factor allocation, and institutional support. This interpretation is consistent with household-level evidence showing that mechanization improves income mainly through factor intensification and productivity enhancement rather than through machinery adoption alone [20].

China's institutional and structural conditions provide an important explanation for this finding. Although the Chinese government has strongly promoted mechanization through subsidy programmes and modernization policies, agricultural production remains dominated by fragmented and small-scale farming systems. Under such conditions, scale economies are difficult to realize fully, thereby limiting the income-enhancing effects of machinery investment.

Meanwhile, another important explanation is the structural mismatch between mechanization expansion and agricultural production patterns. In China, mechanization in-

vestment has expanded rapidly not only in major grain-producing regions but also in economically developed and non-grain-oriented areas. However, agricultural machinery tends to generate larger productivity gains in grain-production systems characterized by standardized cultivation, larger operational scales, and stronger demand for labour substitution. In non-grain regions, where agricultural activities are often more fragmented or oriented toward higher-value but less mechanization-intensive production, additional machinery investment may produce weaker productivity and income effects. This mismatch helps explain why mechanization does not exhibit a stable direct income effect at the provincial level despite rapid nationwide expansion. Consequently, mechanization may reduce labour input without necessarily producing substantial income growth at the aggregate provincial level.

The interaction results further indicate diminishing marginal returns to mechanization as agricultural output increases. A plausible explanation is that mechanization has already been widely adopted in high-output regions, implying that additional machinery investment generates smaller incremental productivity gains. In these regions, the major constraints on rural income growth may shift from machinery availability to issues such as agricultural restructuring, market integration, technological upgrading, and factor coordination. By contrast, lower-output regions may still benefit substantially from mechanization through improvements in labour efficiency and production capacity. This interpretation aligns with recent studies emphasizing the heterogeneous effects of mechanization across regions, farm scales, and development stages [20].

The spatial results additionally suggest that cross-regional spillovers are driven more strongly by agricultural production than by mechanization itself. One possible explanation is that agricultural production can generate interregional effects through market integration, trade linkages, and the circulation of agricultural products, whereas mechanization is more dependent on localized institutional arrangements and service systems. Existing research on agricultural production services emphasizes that the effectiveness of mechanization depends heavily on supporting conditions such as machinery service markets, rural infrastructure [17,18]. Therefore, the relatively limited spillover effects of mechanization observed in this study may reflect uneven regional access to supporting institutions rather than an absence of technological value.

Overall, this study contributes to the literature by showing that the relationship between agricultural mechanization and rural income is neither uniform nor unconditional. Rather than functioning as an independent driver of rural income growth, the effectiveness of mechanization appears to depend on agricultural production conditions, production structure, and regional development contexts. The findings further suggest that agricultural production plays a more prominent role than mechanization itself in shaping both local income growth and spatial spillover effects.

At the same time, it is important to distinguish between association, mechanism, and causality when interpreting the results. The fixed-effects and spatial econometric models primarily identify robust empirical associations, while the interaction analyses reveal conditional patterns related to production conditions and agricultural structure. Although the instrumental-variable estimates provide additional supporting evidence, the results should be interpreted as suggestive rather than definitive causal evidence. Therefore, the policy implications are best understood as evidence-informed recommendations rather than direct causal prescriptions.

Apart from afore-mentioned comparison, the findings are also broadly consistent with evidence from other countries, suggesting that the effectiveness of agricultural modernization is often shaped by spatial heterogeneity and regional production conditions rather than by technology alone. For example, studies from Turkey show that agricul-

tural development is strongly influenced by spatial spillovers and regional differences in climate conditions, implying that uniform policy interventions may be ineffective across heterogeneous agricultural regions [31]. Similarly, research in Poland highlights substantial regional variation in agricultural potential and development outcomes, indicating that production capacity, infrastructure, and resource endowments differ considerably across regions [32]. Earlier work on agricultural development in Europe likewise emphasizes that agricultural production and rural development are increasingly differentiated across regions and therefore require spatially coordinated policy approaches [33].

Compared with these international studies [11,34], the Chinese case examined in this study reveals a similar pattern, the income implications of mechanization depend heavily on local production structures and regional conditions. However, this study further shows that agricultural production generates stronger spatial spillover effects than mechanization itself and that the effectiveness of mechanization varies systematically across grain-oriented and non-grain agricultural systems. These findings suggest that spatial heterogeneity and production conditions may represent common constraints on agricultural modernization across different institutional and geographic contexts.

Despite these contributions, several limitations should be acknowledged. First, the analysis relies on provincial-level panel data, which may mask substantial within-province heterogeneity in farm structure, market accessibility, and institutional conditions. Therefore, the estimated coefficients should be interpreted as average macro-level relationships rather than precise structural effects. Second, the measurement of agricultural mechanization is necessarily imperfect. The mechanization index captures machinery power relative to sown area but does not fully reflect actual machinery utilization, service availability, crop-specific suitability, or mechanization quality. Although robustness tests using total machinery power yield similar results, future research could benefit from more detailed measures of mechanization. Third, although fixed-effects, spatial econometric models, and instrumental-variable estimation help mitigate endogeneity concerns, they cannot completely eliminate potential bias arising from reverse causality and omitted variables. In particular, diesel-price shocks may affect rural income through broader production and transportation channels in addition to mechanization. Therefore, the IV results should be interpreted as supportive rather than definitive causal evidence.

Finally, the transmission channels analysis remains incomplete. Mechanization is likely embedded within a broader process of rural structural transformation involving labour migration, land consolidation, technological diffusion, and market integration. Future research combining household-level and regional-level data would be valuable for clarifying these transmission channels. In addition, although year fixed effects help account for nationwide inflation and price-level changes, future research could further examine the robustness of the results using inflation-adjusted monetary variables expressed in constant prices.

6. Conclusions

This study examines the impact of agricultural mechanization on rural income using provincial panel data from China. By combining a two-way fixed effects model with a Spatial Durbin Model (SDM), the analysis incorporates both regional heterogeneity and spatial dependence. Interaction effects are further introduced to examine the conditional relationship between mechanization and agricultural production. The findings provide a more nuanced understanding of how mechanization affects rural income under different production and regional conditions.

The main conclusions are as follows.

First, agricultural mechanization does not exhibit a stable independent association with rural income. Although mechanization is positively associated with income in the baseline specification, this relationship becomes statistically insignificant after controlling for agricultural production and other covariates. By contrast, agricultural production remains consistently significant, suggesting that production conditions play a more important role in explaining rural income differences.

Second, the relationship between mechanization and rural income appears to be conditional on production conditions. The interaction results indicate that the association between mechanization and income varies with the level of agricultural production, implying that the effectiveness of mechanization is closely related to the broader production environment in which it is deployed.

Third, the results are consistent with diminishing marginal returns to mechanization. In regions characterized by relatively high levels of agricultural production, additional mechanization is associated with smaller income gains, suggesting that machinery expansion alone may be insufficient to sustain continued rural income growth.

Fourth, the findings suggest the existence of a structural mismatch in mechanization allocation. Mechanization expansion is increasingly associated with regions characterized by lower grain-production shares, whereas the estimated interaction effects indicate that mechanization tends to perform relatively better in grain-oriented agricultural systems. This pattern may partly explain the weak and unstable income effect of mechanization observed at the aggregate level.

Fifth, rural income exhibits significant spatial dependence. However, the spatial-effect analysis indicates that agricultural production generates stronger spillover effects than mechanization itself, suggesting that regional production linkages and market integration may play a more important role in cross-regional income transmission.

Overall, the evidence suggests that agricultural mechanization should be understood as a conditional and complementary factor rather than an independent driver of rural income growth. Its observed effectiveness appears to depend on agricultural production conditions, production structure, and regional development contexts. While the results provide useful evidence regarding the mechanization–income relationship, they should be interpreted as identifying robust empirical associations rather than definitive causal effects.

7. Policy Implication

The findings suggest that policies promoting agricultural mechanization should move beyond a technology-centered approach and place greater emphasis on the broader agricultural production system. Since agricultural production appears to play a more important role than mechanization itself in explaining rural income differences, improving production capacity should remain a central policy priority. In particular, efforts to promote moderate-scale land management, strengthen agricultural service systems, and improve access to productive resources may enhance the effectiveness of mechanization and help farmers translate technological inputs into productivity gains.

The results also indicate that the effectiveness of mechanization depends on local production structures. Therefore, machinery investment and mechanization support policies should be better aligned with regional agricultural conditions, especially in major grain-producing areas where mechanization appears to generate relatively stronger benefits. Improving the match between machinery allocation and production demand may help reduce inefficiencies associated with uniform expansion strategies.

Finally, the spatial analysis highlights the importance of regional production linkages and market integration. Because agricultural production generates stronger spillover effects than mechanization itself, policies that strengthen interregional agricultural markets,

logistics networks, and supply chains may contribute not only to local productivity growth but also to broader regional rural development. Given substantial regional heterogeneity in agricultural conditions, differentiated and place-based rural revitalization strategies are likely to be more effective than one-size-fits-all policy approaches.

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