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The Impact of Technological Progress and Industrial Structure Upgrading on Agricultural Economic Resilience: An Empirical Study in China

Changyu Ren [1], Weizhong Liu [1,*], Tong Xiao [1], Alessandra Castellini [2] and Giulia Maesano [2,*]

[1] College of Economics and Management, Xinjiang Agricultural University, Urumqi 830052, China; 320233305@stu.xjau.edu.cn (C.R.); 320223253@stu.xjau.edu.cn (T.X.)

[2] Department of Agricultural and Food Sciences, University of Bologna, Viale Fanin 50, 40127 Bologna, Italy; alessandra.castellini@unibo.it

* Correspondence: lwz@xjau.edu.cn (W.L.); giulia.maesano2@unibo.it (G.M.)

Abstract

Technological advancements are a key engine for improving productivity and are fundamental to enhancing the resilience of the agricultural economy by influencing production methods and driving structural transformation. The objective of this study is to analyze the impact of technological progress on agricultural economic resilience in China, with particular attention to (i) its direct effects on resistance, recovery, and reconstruction; (ii) its indirect effects through the upgrading of the agricultural industrial structure; and (iii) its potential nonlinear effects under different structural thresholds. To achieve this, a multidimensional evaluation framework has been developed to assess agricultural economic resilience through three distinct dimensions: resistance, recovery, and reconstruction. Using fixed effects, mediation, threshold and spatial Durbin models, we empirically analyze the impact pathways. The results suggest that technological progress significantly increases agricultural resilience, with robustness confirmed by various tests including model substitution and variable replacement. Furthermore, regional heterogeneity is evident, with the central region showing the strongest positive effect. The mediation analysis shows that modernization of industrial structure serves as an important transmission channel, while the threshold regression identifies nonlinear effects, with significant improvements occurring beyond certain structural thresholds. The results underline the importance of promoting technological innovation in agriculture, developing region-specific support measures and accelerating structural optimization to strengthen the resilience of agriculture.

Keywords: agricultural economic resilience; technological progress; upgrading of industrial structure; threshold effect

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1. Introduction

Agriculture is a cornerstone for maintaining national stability and safeguarding economic security, particularly when confronted with increasing environmental pressures and socio-economic challenges.

At the international level, resilience has been widely discussed as the ability of systems to absorb, adapt, and transform in response to shocks, emphasizing not only productivity but also ecological and social sustainability [1,2]. In agricultural economics, resilience frameworks have been increasingly applied to evaluate farming systems under conditions of uncertainty and global change [3,4].

In China, agriculture is not only a fundamental sector but also a strategic pillar for sustainable development. As the country strives to transition to high-quality economic growth, enhancing the capacity and robustness of its agricultural economy has become an urgent policy priority [5].

As a key stabilizer and strategic foundation, agriculture underpins the long-term sustainable growth of China's economy, and strong industrial resilience is an important content in building an agricultural power [5]. Resilience can be described as the capacity to absorb and adapt to shocks and disruptions [6]. Agricultural resilience refers to the ability of farming systems to resist and adapt when confronted with diverse and complex external environmental pressures [7]. From the 2022 Central Document No. 1 of the Central Committee of the Communist Party of China (CPC) on stabilizing the basic agricultural market and actively responding to various risks and challenges as well as sudden and serious difficulties at home and abroad to the 2022 Report of the 20th National Congress of the CPC, the Chinese Communist Party's (CCP) policy addressing agricultural resilience has been increasingly shaped by the strategic priorities of the Chinese Communist Party (CCP). The report of the 20th National Congress emphasizes the enhancement of resilience and security across industrial and supply chains, making clear the importance attributed by the Party's Central Committee to reinforcing the agricultural economy and the urgency of implementing effective measures. At the same time, China is undergoing rapid technological transformation, with its growth model progressively evolving from one mainly driven by factor inputs to one propelled by technological advancement. As a major driver of industrial expansion and socio-economic development [8], technological progress has assumed a decisive role within the agricultural sector.

In 2022, China achieved significant advancements in agricultural science and technology, with scientific and technological progress contributing 62.4% to agricultural development, underlining the pivotal role of innovation in driving the modernization of the sector. During the same period, the level of agricultural and crop mechanization also improved substantially, with the overall mechanization rate reaching 73%. This expansion of mechanization has greatly enhanced production efficiency and provided strong support for agricultural modernization. Furthermore, the Central Committee's No. 1 Policy Document of 2024 outlines strategic priorities aimed at strengthening agricultural science and technology, emphasizing the need to optimize the national framework for innovation in this field, so that technological progress continues to play a leading role in advancing agricultural development while bolstering resilience and fostering high-quality growth in the agricultural economy.

At present, global research on agricultural economic resilience remains at an early stage, with most studies concentrating on two main areas. First, drawing on the core concept of agricultural economic resilience, scholars have developed indicator systems from different perspectives, ranging from a single dimension of resistance [9] to two dimensions incorporating both resistance and reconstruction [7], and to three dimensions encompassing resilience, adjustment, and innovation [10]. For example, some researchers have applied the PSR model to assess the resilience of the agricultural economy in Anhui Province [11]. Second, attention has been devoted to identifying the factors that influence agricultural economic resilience. Previous studies indicate that the integration of rural industries [12], crop diversification, and diversification of agricultural production [13,14], together with technological advancement in agriculture [15], all contribute to enhancing resilience. Among these, the development of science and technology and the degree of mechanization emerge as the most critical determinants of agricultural economic resilience [11], while innovation itself is recognized as a key driving force enabling systems to withstand shocks and recover [16].

In exploring effective approaches to strengthen the resilience of the agricultural economy, researchers have examined the issue through the lens of industrial chains [17] and industrial structure [18]. These studies have shown that a diversified and interconnected industrial structure is a critical determinant of industrial resilience [19], and that producer services play an essential role in facilitating industrial upgrading to enhance resilience [20]. As a result, agricultural economic resilience has gradually emerged as a significant topic within agricultural economics. This raises key questions: Can technological progress—recognized as a major driver of agricultural modernization—enhance agricultural economic resilience by improving productivity and strengthening the capacity to manage risks, thereby supporting the stability of agricultural development? Furthermore, how does the upgrading of the agricultural industrial structure—a vital strategy for increasing competitiveness and adapting to market demands—contribute to building resilience? In response to these questions, the present study investigates the effect of technological progress on economic resilience, with a particular focus on clarifying the interrelationships between technological progress, the upgrading of the agricultural industrial structure, and the resilience of the agricultural economy. In addition to testing the overall relationship, we also explore regional heterogeneity (eastern, central, western China) as an important extension, recognizing that uneven institutional and structural conditions may lead to differentiated resilience effects.

2. Theoretical Framework and Research Hypothesis Development

It is necessary to return to the conceptual foundations of "resilience" and "technological progress". Drawing on Holling's (1973) ecological resilience framework [21] and the subsequent Panarchy model [22], resilience is typically described as encompassing three key dimensions: resistance (the capacity to absorb shocks), recovery (the ability to return to previous levels of function), and reconstruction or transformability (the capacity to reorganize and innovate by moving away from previous trajectories). In this study, "technological progress" is understood as the process through which agricultural productivity, production efficiency, and risk management capacity are enhanced via the development, diffusion, and application of new technologies. It encompasses innovations in machinery and equipment, improved crop varieties, precision agriculture, digital and information technologies, and environmentally sustainable practices. These advances influence agricultural economic resilience by strengthening resistance to shocks, accelerating recovery after disturbances, and supporting reconstruction through structural transformation and innovation.

Beyond economic outcomes, resilience in agriculture is also closely connected to ecological performance. International studies underline that technological innovation and structural upgrading can enhance ecosystem services, reduce environmental pressures, and contribute to the long-term sustainability of farming systems [23,24]. For example, precision agriculture and ecological intensification strategies are recognized as pathways to strengthen both the adaptive capacity of farms and their environmental sustainability [15].

In this study, the direct influence of technological progress on agricultural economic resilience is examined across these three dimensions: resistance, recovery, and reconstruction.

To begin with, technological progress strengthens agriculture's ability to withstand risks. From the perspective of innovation theory, advances in technology expand opportunities for agricultural innovation, and the rapid diffusion of new techniques creates "redundancy and diversity" within the system as a form of defense [23]. Lin et al. [13] argued that crop diversification, as an adaptive management approach to environmental change, aligns with the system diversity formed by technology diffusion, jointly providing support for agricultural risk prevention. Research, development, and the application of improved varieties and technologies allow agricultural production to better cope with threats such as natural disasters, pests, and diseases. For instance, the introduction of highperforming crop varieties that are tolerant to insects, disease, and drought can reduce yield losses caused by environmental stress, thereby lowering production risks and enhancing the stability of agricultural outputs.

Secondly, technological progress enhances agriculture's capacity to absorb and recover from shocks. Following natural disasters or other emergencies, modern agricultural technologies can significantly speed up the restoration of production systems. For instance, advanced techniques such as soil remediation and bioremediation can be used to rehabilitate degraded ecosystems on farmland. Moreover, the application of agricultural information technologies provides real-time data that supports recovery efforts, enabling farmers and agricultural organizations to respond more effectively to disasters and to quickly re-establish production [25].

Thirdly, technological progress contributes to strengthening the reconstruction capacity of agricultural systems. From an economic perspective, production function theory shows that the efficiency of agricultural output is directly influenced by the level of technological advancement. The integration of innovative smart farming equipment—such as autonomous tractors and drone-assisted spraying systems—together with precision technologies, streamlines the production process, enhances labor productivity, and ultimately improves the system's ability to reorganize and rebuild.

On this basis, the first hypothesis (H1) is proposed:

H1. *Advancements in technology exert a positive influence on agricultural economic resilience.*

Technological progress promotes a more efficient allocation of production factors across industries and encourages the redistribution and movement of resources [26]. This process strengthens the interconnections along the agricultural industry chain and supports the evolution of the agricultural industrial structure towards greater coordination and rationalization. Moreover, advances in technology guide the direction of capital flows, stimulate the emergence of capital-intensive sectors, and foster the creation of innovative, competitive models and new business formats. These dynamics inject renewed vitality into the growth of the agricultural economy [27] and actively drive the process of structural upgrading in the agricultural sector.

Accordingly, the following hypothesis is formulated:

H2. *Technological progress exerts a positive impact on the upgrading of the agricultural industrial structure.*

The upgrading of the agricultural industrial structure contributes to diversification within agriculture, leading to a broader range of agricultural products and production systems. This diversification enhances production efficiency and generates positive economic effects [8,28], thereby improving the sector's ability to withstand external shocks and recover from them. Additionally, as the structure of the agricultural industry evolves, there is increased emphasis on ecological balance, which strengthens agriculture's ecosystem services, fosters sustainable agricultural development, and increases the system's adaptability to climate and environmental variability.

Hence, the next hypothesis is proposed:

H3. *Upgrading the agricultural industrial structure has a significant positive impact on agricultural economic resilience.*

The application of scientific and technological innovations and advanced methods facilitates the absorption and integration of key innovation factors, enabling the widespread diffusion and penetration of agricultural technologies. This process drives the upgrading of traditional agricultural sectors [29] and encourages the inflow of innovative talent and labor into the agricultural domain [30], thereby improving agricultural economic resilience [29]. Therefore, the fourth hypothesis is presented:

H4. *The upgrading of the agricultural industrial structure mediates the relationship between technological progress and agricultural economic resilience.*

At the early stages of development, when the agricultural industrial structure remains underdeveloped, production efficiency in the sector tends to be low and the allocation of resources is suboptimal. Under these conditions, technological progress cannot fully exert its potential in practical applications. As the structure of the agricultural industry gradually becomes more optimized and upgraded, however, production efficiency improves, resource allocation becomes more rational, and both the scope and effectiveness of technological innovations increase.

On this basis, the fifth hypothesis is proposed:

H5. *The upgrading of the agricultural industrial structure acts as a key threshold condition for technological progress to enhance agricultural economic resilience.*

To sum up, we have established the Theoretical framework diagram, as shown in Figure 1.

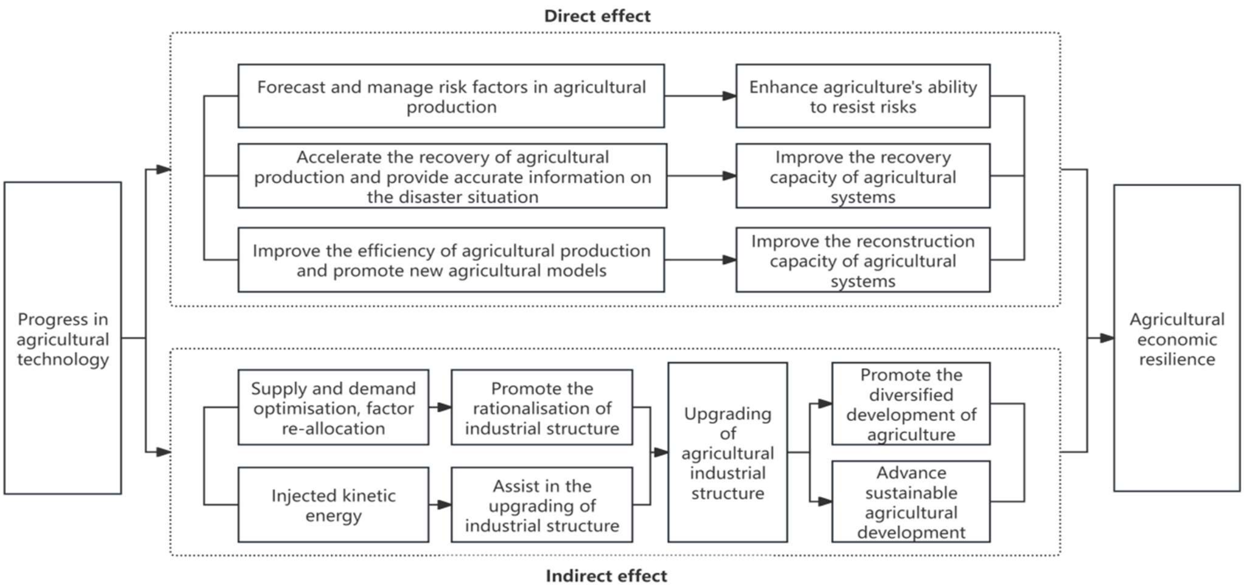

Figure 1. Theoretical framework.

3. Variable Selection and Model Setting

3.1. Data Source and Variable Selection

Considering data availability and reliability, this study makes use of panel data covering 30 provincial-level administrative divisions in China for the period 2013–2022, (excluding Hong Kong, Macao, Taiwan, and Tibet) to explore the impact of technological progress and agricultural industrial structure upgrading on agricultural economic resilience. Due to systematic missing values in multiple core indicators during the period 2013–2022, this study only used data from all provincial-level administrative units in Mainland China, excluding Tibet. Meanwhile, the Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Region were excluded, as their statistical systems are not comparable with that of the Mainland. The data mainly comes from authoritative publications such as the China Statistical Yearbook (CSY), the China Rural Statistical Yearbook (CRSY) and the China Agricultural Machinery Industry Yearbook (CAMIY). For missing values, the interpolation method was employed for imputation to ensure the completeness of the data.

3.1.1. Dependent Variable

The selection of indicators and data sources builds primarily on the studies by Hao et al. [12] and Jiang et al. [5]. A comprehensive index system for evaluating agricultural economic resilience is developed, encompassing three dimensions: resistance, recovery, and reconstruction (see Table 1). The measurement is carried out using the Entropy-Weighted method. For the three sub-dimensions (resistance, recovery, and reconstruction) separately, the hierarchical entropy weight method is employed.

Resistance captures the capacity of the agricultural system to minimize the impact of unexpected events. It is assessed using seven indicators: per capita agricultural output value, agricultural machinery power per unit area, the proportion of disaster-affected area, Engel coefficient of rural households, rural consumption capacity, per capita grain yield, and the effective irrigation rate.

Recovery reflects the ability of the system to recover after a disturbance. This dimension is evaluated through four indicators: the growth rate of primary industry output value, the share of employment in the primary industry, the per capita disposable income of rural residents, and the consumption level of rural households.

Reconstruction represents the system's capability to adjust and transform itself following a shock, focusing on knowledge accumulation, technological innovation, and improvements in production models. It is measured by three indicators: the intensity of fiscal support for agriculture, rural education level, and the proportion of investment in science and technology.

Table 1. Comprehensive framework of indicators for assessing agricultural economic resilience.

Target Dimension	Indicator	Indicator Interpretation	Indicator Attribute	Weights
Resistance	per capita agricultural output value	Output value of the primary industry/Number of people employed in agriculture	Positive	0.075
	Agricultural machinery power density	Total agricultural machinery power/Crop sown area	Positive	0.070
	Proportion of disaster-affected area	Area affected by disasters/Total disaster area	Negative	0.027
	Engel coefficient of rural households	Proportion of food expenditure in total household consumption	Negative	0.015
	Rural consumption capacity	Share of rural retail sales in total social retail sales	Positive	0.070
	Per capita grain yield	Total grain output/Total population	Positive	0.124
	Effective irrigation rate	Effective irrigated area/Crop sown area	Positive	0.076
Recovery	Growth rate of primary industry output	Growth rate of output value in the primary industry	Positive	0.017
	Share of employment in primary industry	Number of people employed in the primary industry/Rural population	Positive	0.043
	Per capita disposable income of rural residents	Average disposable income of rural residents	Positive	0.073
	Rural household consumption level	Per capita consumption expenditure of rural residents	Positive	0.213

Table 1. *Cont.*

Target Dimension	Indicator	Indicator Interpretation	Indicator Attribute	Weights
Reconstruction	Intensity of fiscal support for agriculture	Agricultural, forestry, and water expenditure/Total fiscal expenditure	Positive	0.047
	Rural education level	Educational attainment in rural areas	Positive	0.019
	Proportion of investment in science and technology	Expenditure on science and technology /Total fiscal expenditure	Positive	0.131

3.1.2. Core Explanatory Variable

Technological progress (TePro). Following the approach of Ouyang et al. [31], this study uses the ratio of research and development (R&D) expenditure to regional GDP as a proxy indicator for measuring the level of technological progress.

3.1.3. Mediating and Threshold Variables

Agricultural industrial structure upgrading (Ins).

The upgrading of the agricultural industrial structure is a gradual transformation process, reflected in the shift from a primary-stage structure toward a more advanced and sophisticated configuration. The core objective is to guide the evolution of the structure in a more efficient and rational direction [32]. Building on the methods proposed by Gan et al. [26], Gao [33], and Liu [34], this study constructs an index for agricultural industrial structure upgrading (Ins) by combining a rationalization index (TL) with an optimization index (EI), using a weighted approach.

The rationalization index of the agricultural industrial structure (TL) serves as a key measure for assessing the coordination among sub-industries and the efficiency of resource allocation within the agricultural system. It is commonly calculated using the Theil index, following the formula:

$$\mathrm{TL} = \sum_{i=1}^{n} \left(\frac{y_i}{y}\right) \ln\left(\frac{y_i}{l_i} / \frac{y}{l}\right) \tag{1}$$

$\mathbf{y}$ and $\mathbf{y_i}$ denote the total output value of agriculture, forestry, animal husbandry, and fisheries, as well as the respective output values of each sub-sector, $\mathbf{l}$ and $\mathbf{l_i}$ are the total number of laborers in agriculture, forestry, animal husbandry and fishery and the number of laborers in each sub-sector, respectively. Since it is impossible to accurately obtain the number of laborers in each sub-sector, the value added realized by unit intermediate consumption of agriculture, forestry, animal husbandry and fishery is used to measure the productivity of each industrial sector (y_i/l_i). When the TL value is small, it indicates that the coordination among the sub-sectors in the agricultural system is better, which also means that the agricultural industry structure is more reasonable. When the TL value approaches 0, it means that the labor productivity of each sector is consistent with that of agriculture as a whole, and at this time, the agricultural industrial system has reached the state of internal equilibrium.

The optimization of the agricultural industrial structure (EI) reflects the ongoing process through which the agricultural industry structure evolves toward more advanced stages. Following the approach of Cao et al. [35], this study measures the optimization of the agricultural industrial structure using the share of the output value generated by agricultural, forestry, animal husbandry, and fishery services in relation to the total output value of agriculture, forestry, animal husbandry, and fishery.

3.1.4. Control Variables

Drawing on the relevant work of Meng [28] and other scholars, this study includes as control variables the level of government intervention (Gov): Agriculture is a weak industry, fiscal support for agriculture directly affects the stability of agricultural production and the diffusion of technologies, thereby influencing resilience; infrastructure development (Inf): Highway mileage reflects the accessibility of agricultural areas; improved transportation infrastructure facilitates the transportation of agricultural inputs/outputs and the spread of agricultural technologies, enhancing resilience; urbanization (Urb): Accelerated urbanization leads to the migration of rural labor and capital to cities, which may reduce agricultural production factors and negatively impact resilience; industrial agglomeration (Ina): Agricultural industrial agglomeration generates economies of scale, improves production efficiency, and strengthens the system's ability to resist shocks; and natural disasters (Nat): Disaster-affected area directly shocks agricultural production, which is an exogenous factor that must be controlled when measuring resilience. Detailed definitions of these variables, along with their descriptive statistics, are reported in Table 2.

Table 2. Variable description and descriptive statistics.

Variable Type	Name of Variables	Definition of Variables	Sample Size	Mean Value	Standard Deviation
Variable explained	AgrResi	Entropy weight method is used for measurement	300	0.256	0.068
Core explanatory variable	TePro	R&D expenditure/GDP	300	0.017	0.011
Mediating variable	Ins	0.5 × Rationalization of the industrial structure(TL) + 0.5 × optimization of the industrial structure (EI)	300	0.039	0.028
Control variable	Gov	Agriculture, forestry and water expenditure/GDP	300	0.031	0.020
	Inf	measured by taking the logarithm of highway mileage	300	11.726	0.852
	Urb	Urban resident population/total population	300	0.614	0.114
	Ina	Number of employed persons/area of administrative division	300	0.026	0.040
	Nat	Actual agricultural disaster-affected area/sown area of major crops	300	0.129	0.111

3.2. Model Setting

3.2.1. Benchmark Regression Model

To explore the actual impact of technological progress on agricultural economic resilience, the benchmark model is set as follows:

$$\mathrm{AgrResi}_{it} = a_0 + a_1\mathrm{TePro}_{it} + a_2X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (2)$$

In Equation (2), i represents region, t represents year, $\mathrm{AgrResi}_{it}$ represents agricultural economic resilience; TePro_{it} is the core explanatory variable, indicating technological progress; X_{it} is the relevant control variable, $\mathbf{a_0}$ is the intercept term; μ_i, v_t, ε_{it} represent individual fixed effects, time fixed effects, and random disturbance terms, respectively.

To explore the actual impact of technological progress on each dimension of agricultural economic resilience, the baseline model set up is as follows:

$$\mathrm{Resi}_{it} = b_0 + b_1\mathrm{TePro}_{it} + b_2X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (3)$$

$$\mathrm{Reco_{it}} = \mathrm{c_0} + \mathrm{c_1 TePro_{it}} + \mathrm{c_2 X_{it}} + \mu_\mathrm{i} + \mathrm{v_t} + \varepsilon_\mathrm{it} \quad (4)$$

$$\mathrm{Reson_{it}} = \mathrm{d_0} + \mathrm{d_1 TePro_{it}} + \mathrm{d_2 X_{it}} + \mu_\mathrm{i} + \mathrm{v_t} + \varepsilon_\mathrm{it} \quad (5)$$

In Equations (3)–(5), $\mathrm{Resi_{it}}$, $\mathrm{Reco_{it}}$, and $\mathrm{Reson_{it}}$ respectively represent Resistance, Recovery, and Reconstruction.

Considering the potential spatial correlation of agricultural economic resilience (Y) across provinces, this study first tests spatial dependence using global Moran's I. Given the confirmed positive spatial correlation, the Spatial Durbin Model (SDM) is further employed to address spatial effects and decompose spatial spillover effects of technological progress. The SDM formula is specified as:

$$\mathrm{AgrResi}_{it} = \rho \sum_{j=1, j \neq i}^{N} W_{ij}\mathrm{AgrRes}_{jt} + \alpha_0 + \alpha_1 \mathrm{TePro}_{it} + \alpha_2 \sum_{j=1, j \neq i}^{N} W_{ij}\mathrm{TePro}_{jt} + \alpha_3 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (6)$$

where W_{ij} is the spatial weight matrix (geographical adjacency matrix: $W_{ij} = 1$ if province i and j are adjacent, otherwise $W_{ij} = 0$); ρ is the spatial autocorrelation coefficient.

3.2.2. Mediating Effect Model

Building on Equation (2), the upgrading of the agricultural industrial structure is introduced as a mediating variable to examine the mechanism through which technological progress influences agricultural economic resilience. Accordingly, the following mediation model is specified:

$$\mathrm{Ins_{it}} = \mathrm{e_0} + \mathrm{e_1 TePro_{it}} + \mathrm{e_2 X_{it}} + \mu_\mathrm{i} + \mathrm{v_t} + \varepsilon_\mathrm{it} \quad (7)$$

$$\mathrm{AgrResi_{it}} = \mathrm{f_0} + \mathrm{f_1 TePro_{it}} + \mathrm{f_2 Ins_{it}} + \mathrm{f_3 X_{it}} + \mu_\mathrm{i} + \mathrm{v_t} + \varepsilon_\mathrm{it} \quad (8)$$

In the formula, $\mathrm{Ins_{it}}$ represents the upgrading of industrial structure.

3.2.3. Threshold Effect Model

To further investigate whether the upgrading of the agricultural industrial structure generates a threshold effect in the relationship between technological progress and agricultural economic resilience, the following threshold model is formulated:

$$\mathrm{AgrResi_{it}} = \mathrm{g_0} + \mathrm{g_1\ TePro_{it}\ I(Ins_{it}} \leq \gamma) + \mathrm{g_2\ TePro_{it}\ I(Ins_{it}} > \gamma) + \mathrm{g_3\ X_{it}} + \mu_\mathrm{i} + \mathrm{v_t} + \varepsilon_\mathrm{it} \quad (9)$$

In the formula, I denotes the indicative function, $\mathrm{Ins_{it}}$ is the threshold variable, γ represents the threshold value.

4. Analysis of Empirical Results

4.1. Benchmark Regression Results

Table 3 reports the baseline empirical results for the relationship between technological progress and agricultural economic resilience. The Hausman test yields a statistic of 14.31 with a p-value of 0.026 ($p = 0.026 < 0.05$), indicating that the fixed-effects model is preferred. As shown in Column (2), the estimated coefficient for technological progress (TePro) is 1.019, which is positive and statistically significant at the 1% level. This result demonstrates that technological progress exerts a significant positive effect on agricultural economic resilience, thereby confirming Hypothesis H1. In line with the previous analysis, a plausible explanation is that technological advances enhance production efficiency and the quality of agricultural outputs, improve the ability of the agricultural system to withstand risks, optimize resource allocation, and promote better integration of biological and environmental factors—collectively reinforcing the resilience of the agricultural system.

Moreover, technological progress can transform farmers' production methods and lifestyles, thereby enhancing the capacity of agricultural systems to reorganize and adapt.

For these reasons, technological innovation emerges as a key driver of stronger agricultural economic resilience.

The results also show that the level of infrastructure (Inf) has a significant positive effect on agricultural economic resilience [11], primarily because adequate infrastructure provides the essential physical conditions needed to ensure stable agricultural production.

Conversely, the estimated coefficient for urbanization (Urb) is significantly negative [29]. This may be attributed to a "crowding-out effect" caused by the migration of factors between urban and rural areas: as urbanization accelerates, a large number of rural inhabitants move to cities, leading to a decline in the availability of labor and agricultural resources in rural areas, which in turn negatively influences agricultural economic resilience.

By contrast, the coefficient for industrial agglomeration (Ina) is significantly positive [20,35]. This suggests that higher levels of industrial clustering support economies of scale, improve production efficiency, and ultimately enhance agricultural economic resilience.

To further decompose the impact of technological progress on different dimensions of resilience, fixed-effects regressions were conducted with resistance, recovery, and reconstruction as dependent variables (see Table 4). The results show that: technological progress exerts a significantly positive driving effect only on resistance, which is 4 times that of recovery and 3.6 times that of reconstruction, while the latter two are statistically insignificant. In terms of goodness of fit, the R^2 of the regression for resistance (0.862) is much higher than that of the other two dimensions, indicating that technological progress has the strongest explanatory power for shock resistance capacity.

This difference aligns with theoretical logic: Resistance depends on indicators directly improvable by technology, such as agricultural machinery density and effective irrigation rate; in contrast, Recovery relies on short-term policy compensation, and Reconstruction requires long-term technology transformation, so the immediate effect of technological progress has not yet been manifested.

Table 3. Impact of technological progress on agricultural economic resilience: benchmark regression.

Variables	(1)	(2)	(3)
	Fixed-Effects Regression	**Fixed-Effects Regression**	**Random Effect Regression**
TePro	0.862 *** (0.335)	1.019 *** (0.340)	1.105 *** (0.340)
Gov		0.262 (0.263)	0.025 (0.241)
Inf		0.038 * (0.023)	0.001 (0.011)
Urb		−0.291 *** (0.096)	−0.030 (0.074)
Ina		1.233 ** (0.582)	0.590 ** (0.258)
Nat		0.003 (0.014)	0.003 (0.015)
Individual effect	Controlled	Controlled	—
Time effect	Controlled	Controlled	—
_cons	0.196 *** (0.006)	−0.122 (0.254)	0.189 (0.140)
N	300	300	300
R2	0.79	0.80	0.79

Note: Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses.

Table 4. The regression results of technological progress on various dimensions of agricultural economic resilience.

Variables	Resistance	Recovery	Reconstruction
	Fixed-Effects Regression	**Fixed-Effects Regression**	**Fixed-Effects Regression**
TePro	1.713 *** (0.385)	0.415 (0.639)	0.475 (0.874)
Gov	0.278 (0.297)	0.222 (0.494)	0.297 (0.675)

Table 4. *Cont.*

Variables	Resistance	Recovery	Reconstruction
	Fixed-Effects Regression	Fixed-Effects Regression	Fixed-Effects Regression
Inf	0.032 (0.026)	−0.020 (0.043)	0.152 ** (0.059)
Urb	−0.541 *** (0.109)	−0.413 ** (0.181)	0.508 ** (0.247)
Ina	2.061 *** (0.658)	0.540 (1.094)	0.526 (1.495)
Nat	−0.008 (0.016)	0.001 (0.027)	0.034 (0.037)
Individual effect	Controlled	Controlled	Controlled
Time effect	Controlled	Controlled	Controlled
_cons	0.072 (0.287)	0.563 (0.477)	−1.779 *** (0.652)
N	300	300	300
R2	0.862	0.334	0.287

Note: Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses.

4.2. Test of Spatial Dependence and Spillover Effects

Table 5 shows that the global Moran's I values for the dependent variable (Y) between 2013 and 2022 are consistently positive, with *p*-values highly significant at the 0.1% level ($p < 0.001$) across all years. This provides robust evidence that Y displays notable and stable positive spatial correlation in its geographic distribution: provinces with high-Y values tend to be geographically adjacent to other high-Y provinces, while those with low-Y values tend to cluster alongside other low-Y regions. Such spatial dependence underscores the necessity of spatial econometric analysis—traditional OLS estimation would introduce biases if spatial effects were not accounted for.

Therefore, the Spatial Durbin Model (SDM) was employed to further examine spatial spillover effects, and its results are reported in Table 6. A key advantage of the SDM is its ability to decompose the core explanatory variable (TePro, labeled as x) into three components: direct effect, indirect effect (i.e., spatial spillover effect), and total effect on Y. The spatial autocorrelation coefficient (rho) is estimated at 0.245, which is highly significant at the 1% level ($z = 3.29$). This finding reaffirms that Y maintains significant spatial dependence even after controlling for other variables, meaning the Y values of neighboring regions have a positive influence on the local Y value.

An analysis of TePro's effects shows that its direct effect is significantly positive at the 1% level: when other factors are held constant, a 1-unit rise in local TePro leads to a direct average increase of 0.953 units in local Y. More notably, its indirect effect is also significantly positive at the 1% level, indicating a strong positive spatial spillover. Specifically, a 1-unit increase in local TePro drives an average increase of 2.609 units in Y across all neighboring regions via spatial transmission mechanisms—with the spillover effect being far larger than the direct effect.

Table 5. Moran Index 2013–2022.

Year	I	E(I)	sd(I)	z	*p*-Value
2013	0.584	−0.034	0.123	5.03	0.000
2014	0.572	−0.034	0.123	4.943	0.000
2015	0.523	−0.034	0.124	4.514	0.000
2016	0.505	−0.034	0.124	4.359	0.000
2017	0.529	−0.034	0.124	4.562	0.000
2018	0.417	−0.034	0.123	3.683	0.000
2019	0.417	−0.034	0.121	3.728	0.000
2020	0.479	−0.034	0.123	4.173	0.000
2021	0.491	−0.034	0.123	4.267	0.000
2022	0.412	−0.034	0.121	3.691	0.000

Note: I = global Moran index; *p*-value < 0.001 indicates significance at the 1% level.

Table 6. Test results of spatial spillover effect.

Variables	Wx	Direct Effect (LR_Direct)	Indirect Effect (LR_Indirect)	Total Effect (LR_Total)
TePro	1.874 *** (2.74)	0.953 *** (2.95)	2.609 *** (2.92)	3.563 *** (3.61)
Gov	−0.577 (−1.37)	0.459 * (1.88)	−0.575 (−1.16)	−0.115 (−0.23)
Inf	−0.026 (−0.47)	0.035 (1.58)	−0.014 (−0.21)	0.021 (0.25)
Urb	−0.145 (−0.75)	−0.184 * (−1.90)	−0.242 (−1.00)	−0.426 * (−1.67)
Ina	−2.148 ** (−2.13)	1.017 * (1.95)	−2.474 ** (−2.00)	−1.457 (−1.05)
Nat	0.002 (0.07)	0.005 (0.36)	0.004 (0.13)	0.009 (0.25)
Spatial Autocorrelation (rho)	—	—	—	0.245 *** (3.29)
Observations	300	300	300	300
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: The values in parentheses are z statistics; Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively.

4.3. Robustness Test

4.3.1. Replacement Regression Model

Given that agricultural economic resilience satisfies the requirements of a restricted dependent variable model, a Tobit model is employed to reassess the effects. As presented in Column (1) of Table 7, the estimation results obtained using this alternative specification are consistent with the baseline findings: technological progress continues to exert a significant positive influence on agricultural economic resilience at the 1% level, confirming the robustness of the regression results.

Table 7. Robustness test.

Project	(1)	(2)	(3)
	Tobit Model	Replace the Core Explanatory Variables	Samples of Municipalities Directly Under the Central Government Are Excluded
TePro	1.577 *** (0.481)	0.010 *** (0.002)	1.996 *** (0.684)
Variable of control	Controlled	Controlled	Controlled
Individual effect	Uncontrolled	Controlled	Controlled
Time effect	Uncontrolled	Controlled	Controlled
_cons	−0.202 *** (0.066)	−0.227 (0.240)	0.047 (0.304)
N	300	300	260
R2	—	0.82	0.80

Note: Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses.

4.3.2. Replace the Core Explanatory Variables

Following the approach proposed by Wei et al. [36], this study uses the level of mechanization as a proxy variable for agricultural technological progress, specifically measured as the total machinery power per agricultural worker (i.e., the ratio of total machinery power to the number of employees in the primary industry). As shown in Column (2) of Table 7, the results indicate that technological progress exerts a significant positive effect on agricultural economic resilience at the 1% level. This demonstrates that, even when the core explanatory variable is replaced, technological progress continues to enhance agricultural economic resilience, confirming the robustness and reliability of the regression findings.

4.3.3. Exclude the Samples of Municipalities Directly Under the Central Government

Given the substantial differences between municipalities (Beijing, Tianjin, Shanghai, Chongqing) and other provinces in terms of rural labor structures and agricultural economic development—since municipalities, as urban agglomerations, have a predominance of rural labor employed in non-agricultural sectors, whereas other provinces retain more traditional agricultural labor patterns—the samples corresponding to municipalities were excluded for re-analysis. The results, presented in Column (3) of Table 7, indicate that the estimated coefficient for technological progress is 1.996 and remains significantly positive at the 1% level, confirming the robustness of the regression outcomes.

4.4. Regional Heterogeneity and Mediating Effect Analysis

4.4.1. Regional Heterogeneity Analysis

To further investigate the regional heterogeneity in the impact of technological progress on agricultural economic resilience, the sample was divided into three groups (eastern, central, and western regions) with reference to the economic development levels of provinces, autonomous regions, and municipalities [34]. For details, please refer to Appendix A. The results of this heterogeneity analysis, shown in Table 8, reveal that the estimated coefficients for the eastern and central regions are 1.019 and 4.275, respectively, and are statistically significant at the 10% and 5% levels. In contrast, the effect of technological progress on agricultural economic resilience in the western region is not statistically significant.

Table 8. Regional heterogeneity and mediating effect analysis.

Items	Regional Heterogeneity Analysis			Mediating Effect Analysis		
	(1) East	**(2) Central**	**(3) West**	**(4) AgrResi**	**(5) Ins**	**(6) AgrResi**
TePro	1.019 * (0.558)	4.275 ** (1.687)	0.606 (0.368)	1.019 *** (0.340)	0.966 *** (0.259)	0.702 *** (0.339)
Ins	—	—	—	—	—	0.327 *** (0.080)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Individual effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
_cons	−0.281 (0.530)	−1.193 ** (0.593)	−0.504 * (0.270)	−0.122 (0.254)	0.160 (0.193)	−0.175 (0.247)
N	110	80	110	300	300	300
R2	0.886	0.944	0.972	0.80	0.47	0.81

Note: Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses.

In summary, the influence of technological progress on agricultural economic resilience varies markedly across regions. In the central region, abundant agricultural resources and significant potential for technological advancement create favorable conditions for technological innovations to exert a strong effect on resilience. Meanwhile, the eastern region, supported by advantageous conditions and a series of preferential policies, has achieved a relatively high level of agricultural modernization, enabling technological progress to contribute positively to resilience, albeit to a lesser extent than in the central region. Conversely, the western region faces limitations such as insufficient investment in science and technology and a shortage of resources, which constrain agricultural R&D and the diffusion of innovations. Consequently, technological progress has not produced a significant impact on resilience in this region. These differences highlight the uneven development of the agricultural economy and the unequal application of technological progress across China's regions.

4.4.2. Mediating Effect Analysis

To examine more deeply the relationships among technological progress, the upgrading of the agricultural industrial structure, and agricultural economic resilience, this study applies the stepwise regression coefficient method to test for mediation effects.

In Table 8, Column (4) shows that the direct impact of technological progress on agricultural economic resilience is statistically significant, providing preliminary evidence in support of Hypothesis H1. Column (5) demonstrates that technological progress has a positive and significant effect on the upgrading of the agricultural industrial structure, thereby confirming Hypothesis H2. In Column (6), both technological progress and the upgrading of the agricultural industrial structure remain positively significant at the 1% level; however, the regression coefficient of technological progress decreases from 1.019 to 0.702. This reduction indicates that part of the influence of technological progress on agricultural economic resilience operates indirectly through the upgrading of the agricultural industrial structure, which validates Hypotheses H3 and H4.

4.5. Threshold Effect Test

To examine whether technological progress affects agricultural economic resilience in a nonlinear manner, the upgrading of the agricultural industrial structure is introduced as a threshold variable. A threshold test is conducted using the Bootstrap method to identify both the presence and the number of thresholds [4]. As shown in Table 9, after 300 bootstrap replications, the p-values for the single-threshold and double-threshold tests are 0.017 and 0.003, respectively. These results indicate the presence of a double threshold effect, with estimated threshold values of 0.0165 and 0.1047.

When the upgrading of the agricultural industrial structure crosses these two thresholds, the effect of technological progress on agricultural economic resilience changes significantly, providing support for Hypothesis 5.

Table 9. Results of the threshold effect test.

Threshold Variable	Threshold Number	F Value	p Value	Critical Value			BS Times
				1%	5%	10%	
Ins	Single threshold	40.64	0.017	47.421	32.455	25.381	300
	Double threshold	44.05	0.003	41.833	27.556	20.662	300

As shown in Table 10, when the level of agricultural industrial structure upgrading is below 0.0165, the effect of technological progress on agricultural economic resilience is negative and significant at the 1% level. This suggests that, at the early stages of structural upgrading, the reallocation of resources and the process of technological upgrading may disrupt agricultural production, thereby weakening resilience.

When the level of upgrading falls within the range of 0.0165–0.1047, the effect of technological progress on agricultural economic resilience becomes positive but remains statistically insignificant. This implies that during this transitional phase of structural transformation, new forms of agricultural business begin to emerge, and technological progress starts to have a beneficial influence on resilience; however, this influence is unstable and does not yet reach statistical significance.

Finally, when the upgrading of the agricultural industrial structure exceeds 0.1047, the effect of technological progress on agricultural economic resilience becomes positively significant at the 1% level. At this stage, the structural upgrading of the agricultural industry has reached a relatively advanced level, and new technologies begin to penetrate the agricultural economy more broadly, creating greater opportunities and support for agricultural development.

Table 10. Threshold model estimation results.

Variables	Ins
Din_0	−1.135 *** (0.380)
Din_1	0.134 (0.334)
Din_2	2.782 *** (0.592)
Control Variables	Yes
Fixed Effects	Yes
Constant	−1.177 *** (0.285)
N	300
R^2	0.719

Note: Superscripts ***, ** and * indicate that the estimated value is significant at the level of 1%, 5% and 10%, respectively. Robust standard errors are in parentheses.

5. Discussion

This study examines the mechanisms through which technological progress influences agricultural economic resilience and demonstrates that technological advances exert both direct and indirect effects. Technological progress directly enhances the three dimensions of resilience—resistance, recovery, and reconstruction—while indirectly strengthening resilience by fostering the rationalization and optimization of the agricultural industrial structure. To capture these dynamics, an evaluation index system for agricultural economic resilience was constructed around these three dimensions, and panel data from 30 Chinese provinces for the period 2013–2022 were analyzed to assess the effect of technological progress.

The findings can be summarized as follows: (1) Technological progress significantly improves agricultural economic resilience. This conclusion remains robust across multiple checks, including alternative model specifications, substitution of key explanatory variables, and exclusion of municipalities from the sample; (2) The impact of technological progress on agricultural economic resilience exhibits marked regional heterogeneity: it is strongest in the central region, followed by the eastern region, and weakest in the western region. These differences reflect variations in technological infrastructure, resource endowments, and capacity to adopt innovation. The central region, characterized by abundant agricultural resources and considerable potential for technological upgrading, derives the greatest benefit from innovation-driven improvements in productivity and risk management. By contrast, constraints such as insufficient R&D investment and weaker infrastructure limit the contribution of technological progress to resilience in the western region. The heterogeneity results highlight that the benefits of technological progress are not evenly distributed. This constitutes an additional contribution of this paper, suggesting that policy support should be tailored regionally rather than uniformly. (3) Technological progress enhances resilience by accelerating the modernization of the agricultural industrial structure. By promoting both rationalization and optimization, it facilitates more efficient resource allocation, diversification, and productivity gains, all of which reinforce resilience. (4) Technological progress has heterogeneous effects on different dimensions of agricultural economic resilience: it significantly enhances resistance but exerts no significant impact on recovery or reconstruction. This aligns with the logic that resistance depends on indicators directly improvable by technology, while recovery and reconstruction need coordination with short-term policies or long-term transformation, where technological progress's immediate effect is not yet shown.

The findings are in line with the broader international literature, which highlights that resilience is highly context-dependent and shaped by regional resource endowments, institutional conditions, and environmental constraints [3,37]. Importantly, resilience is not only about economic robustness but also about maintaining ecological balance and promoting sustainable agricultural development [23].

These results are consistent with the findings of Yang et al. [38] and Li & Wan [39]. Yang et al. [38] demonstrate that agricultural technological innovation directly strengthens adaptive and transformative capacities, while Li & Wan [39] confirm the persistent positive association between innovation and resilience across regions. Regarding regional heterogeneity, Yang et al. [38] report stronger effects in eastern and central China—closely matching our conclusion that the central region experiences the largest benefits—while Li & Wan [39] emphasize that less developed areas and non-major grain-producing regions tend to gain more, highlighting the context-specific nature of these effects. Finally, both studies corroborate the mediating role of structural transformation: Yang et al. [38] identify upgrading of the agricultural industrial structure as a key transmission channel, and Li & Wan [39], through their threshold analysis of fiscal support, implicitly show that structural conditions such as industrial maturity modulate the impact of technological inputs. These insights align with our findings that structural upgrading functions both as a mediator and as a threshold variable enabling technology-driven resilience.

In sum, this study underscores the importance of technological progress as a fundamental driver of agricultural economic resilience, enriches the theoretical understanding of resilience in the agricultural context, and offers useful guidance for future efforts to strengthen resilience through innovation.

While this study focuses on the economic dimension of resilience, future research should extend these findings to ecological resilience, an area increasingly recognized as central to sustainable agricultural development. Technological advances not only affect productivity and efficiency but can also reshape ecological interactions, reduce environmental pressures, and enhance the long-term adaptive capacity of agro-ecosystems. Replicating this type of analysis with explicit ecological indicators—such as biodiversity, soil health, or ecosystem service provision—represents an important avenue for future research. In addition, cross-country comparative studies and the use of micro-level farm data could provide further insights into how technological and structural transformations jointly shape resilience in diverse institutional and ecological contexts.

6. Conclusions and Implications

This study examines how technological progress and the upgrading of the agricultural industrial structure influence agricultural economic resilience across 30 Chinese provinces between 2013 and 2022. Using a comprehensive index system based on resistance, recovery, and reconstruction, and applying fixed-effects, mediation, and threshold models, several key conclusions emerge.

First, technological progress significantly enhances agricultural economic resilience. It strengthens the sector's ability to withstand, recover from, and adapt to external shocks, primarily through gains in productivity, efficiency, and risk management capacity. This effect is robust across different model specifications and tests.

Second, technological progress exerts heterogeneous effects on the three dimensions of agricultural economic resilience: it significantly boosts resistance, but has no significant impact on recovery or reconstruction.

Third, the upgrading of the agricultural industrial structure plays a pivotal mediating role in this relationship. Technological progress promotes structural transformation by reallocating resources, encouraging innovation, and advancing higher-value agricultural activities. This structural evolution, in turn, further strengthens resilience.

Fourth, the analysis of regional heterogeneity shows that the positive effect of technological progress is most evident in central China, followed by the eastern region, while it is not statistically significant in the western region. This suggests that differences in technological infrastructure, resource availability, and policy support greatly influence the extent to which technological advancements contribute to resilience.

Fifth, the threshold analysis indicates that the benefits of technological progress become substantially stronger only when the agricultural industrial structure surpasses certain levels of development. This underscores the importance of achieving a minimum level of structural optimization to fully leverage technological advances.

Overall, these findings generate several important policy recommendations:

Strengthen innovation and the promotion of agricultural science and technology.

Governments should increase investment in agricultural scientific and technological innovation, using instruments such as financial subsidies, tax incentives, and public–private partnerships to encourage R&D by enterprises and research institutions. For the resistance dimension, priority should be given to developing and applying technology-sensitive tools that directly enhance shock resistance. For recovery and reconstruction, policies should link technological promotion with short-term compensation mechanisms and long-term infrastructure upgrades, to address the lagged effect of technological progress. Attention should also be given to improving the agricultural extension system by investing in local-level technology transfer services, enhancing farmers' skills in adopting technologies, and increasing the benefits of agricultural production.

Implement regionally differentiated support policies. In provinces in central China (e.g., Henan, Hubei, Hunan), where agricultural resources are abundant and there is considerable room for technological improvement, policies should focus on strengthening innovation, expanding technology adoption, and maximizing the contribution of technological progress to resilience. In the eastern region (e.g., Jiangsu, Zhejiang, Shandong), which is more advanced in terms of modernization, greater emphasis should be placed on integrating agriculture with tourism, culture, and other industries, thereby enhancing resilience by diversifying agricultural functions and value. For western provinces (e.g., Sichuan, Guizhou, Yunnan), in addition to promoting technological innovation, priority should be given to strengthening agricultural infrastructure—such as irrigation systems and transport networks—to create the necessary physical conditions for technological progress to take root. Given the significant spatial spillover of agricultural technological progress, inter-provincial collaboration mechanisms should be established—e.g., joint R&D of agricultural technologies between central and eastern provinces, and technology transfer programs from eastern to western provinces. This will amplify the spillover effect of technological progress and promote coordinated improvement of agricultural economic resilience across regions.

Optimize and upgrade the agricultural industrial structure. Policy should be guided by technological progress to actively drive structural optimization. Specifically, strategies should focus on developing efficient, green, and circular agriculture; improving resource-use efficiency; reducing environmental impacts; and fostering integration between agriculture and other sectors such as tourism and e-commerce. These initiatives will extend the agricultural value chain and raise the added value of agricultural products. Furthermore, strengthening market supervision and building robust information service systems are essential to create a conducive market environment that supports industrial upgrading.

7. Limitations

This study has several limitations that also point to future research opportunities. First, our proxy for technological progress reflects overall regional innovation rather than agriculture-specific R&D inputs; future work could refine this using agricultural patents or sectoral R&D data. Second, despite multiple robustness checks, potential endogeneity cannot be fully ruled out, and instrumental variable strategies would serve as a valuable extension. Third, the analysis is confined to Chinese provincial data; cross-country comparisons may clarify whether the mechanism varies across different contexts. Fourth, our focus on provincial panels overlooks micro-level dynamics, and exploring these could provide more granular policy insights. Finally, we also hope our findings can make marginal contributions to relevant research fields.

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Appendix A

Table A1. List of 30 Provinces and Their Regional Classification.

Regional Classification	Provinces/Municipalities/Autonomous Regions
Eastern	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
Western	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Note: Only samples used for the text are included.

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