Article

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Caihong Ji * and Yulu Wang

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Policy-Based Insurance for Three Major Staple Crops and Agricultural Economic Resilience: Evidence from a Multi-Timepoint Difference-in-Differences Analysis in China

Caihong Ji * and Yulu Wang

School of Economics, Beijing Technology and Business University, Beijing 100048, China
* Correspondence: jich@btbu.edu.cn

Abstract

Enhancing agricultural economic resilience (AER) is essential for global food security. As a key policy tool for stabilizing agricultural production, policy-based agricultural insurance lacks rigorous causal evidence on its impact on resilience. Using 2012–2023 provincial panel data from China, this study measures AER via the entropy method and identifies policy effects using a multi-timepoint difference-in-differences (DID) model. We find that policy-based insurance for the three major staple crops significantly strengthens AER, primarily by promoting agricultural technological innovation (ATI) and regional industrial structure upgrading (RIS). The improvement effects are more pronounced in central and western regions, non-major grain-producing areas, and regions with higher natural risks. Our findings confirm that the staple crop insurance policy effectively boosts agricultural resilience, suggesting that differentiated implementation can support more sustainable and targeted agricultural risk governance.

Keywords: agricultural economic resilience; policy-based agricultural insurance; three major staple crops; agriculture technological innovation; regional industrial structure upgrading; sustainable agriculture

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1. Introduction

Against the backdrop of increasing extreme weather events, market fluctuations, and geopolitical uncertainties, agricultural systems worldwide are facing unprecedented challenges. Sustaining stable agricultural production and ensuring food security have become central to the United Nations Sustainable Development Goals (SDGs). Agricultural economic resilience—defined as the ability of the agricultural system to resist shocks, recover quickly, adapt to changes, and innovate for development—has emerged as a key indicator of sustainable agricultural capacity. Economically resilient agriculture can effectively mitigate losses from natural disasters, stabilize industrial chains, and protect rural livelihoods, thereby supporting long-term food security and ecological sustainability [1].

As the world's largest developing country and a major grain producer and consumer, China has attached great importance to agricultural risk management. Since 2007, policy-based agricultural insurance has been implemented nationwide, and its premium volume has ranked first globally since 2020. In particular, the pilot policy of full-cost insurance and planting income insurance for the three major staple crops (rice, wheat, and corn), launched in 2018 and expanded nationwide in 2023, aims to cover production costs and planting income, fundamentally enhancing farmers' ability to cope with natural and market risks. Despite large-scale promotion, its actual contribution to agricultural economic resilience remains to be rigorously verified.

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Existing studies have explored the effects of agricultural insurance on farmers' income, grain output, and production behavior, but few have regarded agricultural economic resilience as the core outcome variable. Furthermore, most studies use traditional measurement methods and lack rigorous causal identification. Few studies systematically clarify how staple crop insurance enhances resilience through technological progress and structural optimization. Against this gap, this study takes China's staple crop insurance policy as a quasi-natural experiment and uses a multi-timepoint DID model to answer three core questions: (1) Can policy-based insurance for the three major staple crops significantly improve agricultural economic resilience? (2) Through what mechanisms does the policy function? (3) Does the policy effect vary across different regions and risk environments?

The marginal contributions of this study are threefold: (1) Research perspective: We link policy-based staple crop insurance to agricultural economic resilience, expanding the research on agricultural risk governance policy outcomes and resilience drivers. (2) Identification strategy: Using a multi-timepoint DID model, we overcome endogeneity caused by sequential policy promotion and obtain more reliable causal estimates. (3) Mechanism interpretation: We verify two key channels—agricultural technological innovation and regional industrial structure upgrading—revealing how insurance policies transform risk protection into long-term resilience.

The remainder of this paper is organized as follows: Section 2 presents the literature review. Section 3 introduces basic concepts, influence mechanism and research hypotheses. Section 4 describes the methodology, including data, variables, and econometric models. Section 5 reports baseline regression, robustness checks, mechanism analysis, and heterogeneity results. Section 6 discusses the findings against existing literature. Section 7 concludes and provides policy recommendations.

2. Literature Review

2.1. Research on the Implementation Effect of Agricultural Insurance Policy

Agricultural insurance is an important means of agricultural risk diversification and transfer [2], a key component of the rural financial system [3], and a widely used financial tool for supporting agriculture worldwide [4]. Its implementation effects can be summarized from both macro and micro dimensions.

Macro-level effects focus on food security and rural revitalization. Cole found that agricultural insurance alleviates farmers' production risk anxiety and encourages increased grain production input, improving output levels [5]. Jiang and Zhu confirmed a significant positive correlation between agricultural insurance development and national food security, as insurance compensates for staple grain production losses and stabilizes sown areas [6]. Zhou highlighted the risk guarantee role of agricultural insurance in rural revitalization [7], while Shi and Ling clarified that insurance protects farmers' income, stabilizes grain prices, and prevents disaster-induced poverty, supporting the rural revitalization strategy [8].

Micro-level effects center on farmers' income and planting behavior. Hosseini and Gholizadeh proposed that agricultural insurance increases farmers' income and reduces income fluctuation uncertainty [9]. Lu et al. pointed out that insurance directly increases income through loss compensation and indirectly expands income channels by optimizing planting scale and structure [10]. Seamon et al. found that insurance enhances farmers' sustainable operation confidence by compensating for weather-related losses [11], and Jiang et al. confirmed that staple crop policy-based insurance effectively increases farmers' income, especially in western regions [12].

2.2. Research on Agricultural Economic Resilience

The term "resilience" originates from Latin, referring to a system's ability to return to its pre-disturbance state. In 1973, Holling first introduced resilience into ecology, defining it as an ecosystem's ability to maintain core functions and recover balance under disturbances [13]. Reggiani et al. extended resilience to spatial economics [14], and Martin clarified economic resilience as a regional economic system's ability to adapt to external shocks by adjusting development paths [15].

Domestic scholars have further defined economic resilience. Peng et al. defined it as a regional system's ability to resist shocks, adapt, and recover [16]; Su defined agricultural economic resilience as the ability to cope with external disturbances [17]; and Sun and Sun divided it into four dimensions: resistance, recovery, adaptation, and creativity [18]. Folke extended resilience to agriculture, defining agricultural economic resilience as the ability to maintain economic stability and recover under external shocks [19]. Jiang defined it as the systemic attribute of maintaining normal operation and adaptability under multiple risk shocks [20], and Wu and Shi described it as the comprehensive ability to maintain stability and recover under internal and external pressures [21].

Existing studies mainly adopt two methods to measure agricultural economic resilience: core variable method and index system method. The core variable method uses indicators sensitive to economic shocks, such as regional GDP, employment, and agricultural labor productivity. Martin selected GDP and employment to evaluate regional economic resistance and recovery [15], while Song and Liu used agricultural labor productivity to reflect structural adjustment [22].The index system method draws on Martin's Pressure-State-Response (PSR) model [23]. Li et al. constructed an index system for agricultural economic resilience by selecting indicators from three layers: pressure layer, state layer, and response layer, measured regional agricultural economic resilience levels, and evaluated the response ability of the agricultural system facing risks [24].Yu and Zhang found that provincial agricultural economic resilience is rising but with widening inter-regional disparities [25]. Zhang and Hui measured provincial resilience values and confirmed spatial differences [26]. Jiang noted that resilience has spatial spillover effects but lacks coordinated development, and is inversely related to regional economic development [20].

Scholars have examined the determinants of agricultural economic resilience from diverse perspectives. Zhu et al. identified economic development, industrial structure diversity, and communication technology as key influencing factors [27]. Li et al. confirmed that improved agricultural infrastructure enhances resilience with significant regional heterogeneity [28]. Tang and Chen found this positive effect is stronger in major grain-producing areas than in non-major ones [29]. Hao et al. argued that rural industrial integration boosts resilience by driving agricultural growth and optimizing the human capital structure [30]. Based on 2010–2019 provincial panel data, Yan et al. found that population aging significantly weakens resilience by inhibiting agricultural technology application, providing a new perspective for understanding the aging-agriculture relationship [31].

Recently, researchers have focused on the digital economy's impact on agricultural economic resilience. Using spatial econometric models, Zhao and Xu found that the digital economy significantly improves resilience and generates positive spatial spillover effects through industrial structure optimization, with stronger effects in eastern regions and low-urbanization provinces [32]. Sun et al. noted that the digital economy promotes resilience, but this effect is significant in eastern and central provinces and insignificant in western provinces [33].

2.3. Research on the Impact of Agricultural Insurance on Agricultural Economic Resilience

Currently, agricultural economic resilience has become a key research focus, yet studies on how agricultural insurance affects resilience remain limited. Using provincial data and a two-way fixed-effects model, Wang et al. found that China's agricultural economic resilience rose overall with notable regional disparities, and agricultural insurance significantly enhanced resilience with regional heterogeneity [34]. Both Quan et al. and Chen et al. applied the difference-in-differences model and confirmed that the 2018 first-phase pilot of full-cost and revenue insurance exerted a significantly positive effect on agricultural economic resilience [35,36].

Agricultural insurance stimulates higher R&D investment from enterprises, research institutions, and large-scale farmers via risk protection and capital leverage, thereby advancing agricultural technological innovation. Its resource allocation effect also improves agricultural

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production conditions and creates space for technological upgrading [37]. Cofré-Bravo et al. revealed that agricultural technological innovation boosts farmers' income by cutting costs, raising efficiency, and improving product quality, while also increasing grain output and generating positive spatial spillovers to neighboring agricultural systems [38]. Jiang et al. argued that such innovation is a key driver of high-quality development in agricultural economic resilience, promoting farmers' income growth and industrial transformation by optimizing resource allocation [20]. Zhang and Hui noted substantial improvements in provincial agricultural economic resilience during 2009–2018, which they attributed to China's rural reform and agricultural technological innovation [26]. Li and Wan further verified that agricultural technological innovation positively promotes agricultural economic resilience [39].

Agricultural insurance strongly supports the upgrading of the regional industrial structure. From a risk-management perspective, Hao documented that rural financial and insurance services advance regional industrial structure upgrading, which in turn strengthens agricultural economic resilience [40]. Davis argued that agricultural insurance establishes a risk barrier for agricultural production and stabilizes the production environment, encouraging farmers to adopt technological innovation and improve production efficiency [41]. Xiong proposed that agricultural insurance exerts a significantly positive effect on regional industrial structure upgrading by dispersing risks associated with structural transformation and protecting farmers' economic benefits [42].Regional industrial structure upgrading plays a vital role in enhancing agricultural economic resilience. Dai tested the role of advanced regional industrial structure in the relationship between digital inclusive finance and agricultural economic resilience, and found that digital inclusive finance upgrades the regional industrial structure, which improves employment, farmers' capabilities, and risk resilience, thus strengthening agricultural economic resilience [43]. Using a mediating-effect model, Tang and Chen confirmed that agricultural infrastructure enhances agricultural economic resilience by promoting regional industrial structure upgrading [29].

Existing literature has established agricultural economic resilience as a cutting-edge topic in economic research, with extant studies concentrating on its conceptual connotation, measurement approaches, and influencing factors. Research on the implementation effects of agricultural insurance policies has largely centered on food security, rural revitalization, and farmers' income growth. Against rising economic uncertainty, it is necessary to broaden the analytical scope of agricultural insurance policy effects, with a focus on the mechanism through which policy-based agricultural insurance affects agricultural economic resilience, so as to meet the new demands for risk governance capacity in sustainable agricultural development. Nevertheless, studies investigating how policy-based agricultural insurance influences agricultural economic resilience remain scarce. Moreover, existing work only examines the first-phase pilots covering six provinces and cities in 2018, with little attention paid to the impacts of the second-phase pilots launched after 2021. Using provincial panel data from 2012 to 2023 and a multi-timepoint difference-in-differences (DID) model, this paper investigates the effects of the two-phase policy implementation on agricultural economic resilience and further comprehensively assesses the dynamic policy impacts.

3. Basic Concepts and Research Hypotheses

3.1. Basic Concepts

3.1.1. Policy-Based Agricultural Insurance for the Three Major Staple Crops

Policy-based agricultural insurance refers to government-subsidized agricultural insurance, divided into central and local policy-based insurance. It provides farmers with high-level risk protection at low cost, supporting stable agricultural production.

Policy-based agricultural insurance for the three major staple crops refers to policy-based agricultural insurance whose insured subject matter is the three major grain crops: rice, wheat and maize. This study focuses primarily on two types of such insurance: full- cost insurance and planting income insurance for the three major staple crops, whose coverage extends to all farmers including those with moderate-scale operations and smallholder farmers, as well as agricultural production and operation organizations.

Specifically, full-cost insurance is agricultural insurance whose insurance amount covers the total costs of agricultural production, including materialized costs, land costs and labor costs. Its insurance coverage encompasses major local natural disasters, major pests, diseases and rodent infestations, accidents, wildlife damage and other risks. Planting income insurance is agricultural insurance whose insurance amount reflects the prices and yields of agricultural products and whose coverage level covers the planting income of relevant agricultural products. Its insurance coverage compensates for income losses caused by fluctuations in agricultural product prices and yields.

3.1.2. Agricultural Economic Resilience

The concept of resilience originated in engineering, physics, and ecology and was later applied to economics. Agricultural economic resilience (AER) involves social, economic, and environmental dimensions with no unified definition. Folke defined it as agricultural economic stability and recovery capacity under external shocks [19], and Jiang defined it as the ability to maintain normal operation under multiple risks [20].

This paper defines agricultural economic resilience as the capacity of an agricultural economic system to maintain its normal functional operation when exposed to various disaster shocks. It reflects two core capabilities of the system in responding to external disturbances: resistance capacity and recovery capacity.

Specifically, resistance capacity denotes the system's defensive ability against potential risks and uncertainties, which relies on sound risk prevention awareness, mature technical support, and scientific management systems to form a robust risk defense line. Recovery capacity refers to the system's ability to rapidly restore normal operation after suffering functional impairment from shocks; its realization depends on adequate factor reserves for material support, sustained innovation vitality to tackle recovery barriers, and reliable risk management mechanisms for institutional guarantee.

3.2. Influence Mechanism and Research Hypotheses

3.2.1. Direct Impact of Policy-Based Agricultural Insurance on Agricultural Economic Resilience

Policy-based agricultural insurance is designed to mitigate diverse risks in agricultural production. It directly safeguards production activities and systematically enhances the uncertainty resistance of the agricultural system by stabilizing the economic foundation and optimizing production conditions. It provides critical financial support for agricultural reproduction and strengthens the adaptive and recovery capacities of the agricultural system when confronted with external shocks. In short, policy-based agricultural insurance fosters both agricultural economic development and the continuous enhancement of economic resilience.

The core function of agricultural insurance is to compensate for risk-induced losses. When natural disasters or accidents occur, the insurance mechanism acts as an economic buffer for farmers and production activities. By compensating for lost income and production inputs, agricultural insurance effectively sustains farmers' reproduction cycles and mitigates the adverse impacts of disasters on the agricultural economy. This compensation-recovery mechanism is indispensable for maintaining stable economic operation and strengthening external risk defense capabilities. Ding and Sun (2021) noted that agricultural insurance significantly reduces disaster-caused agricultural damage and improves production conditions [44].

Farmers usually make production decisions based on expected income changes. When agricultural risks arise, declining income expectations make farmers more cautious about input. With expanded insurance coverage, farmers' income expectations can be effectively stabilized, creating space for production mode adjustments. Such adjustments include a greater willingness to adopt large-scale operations and introduce new production technologies [45]. These measures optimize

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production conditions, strengthen the agricultural system's ability to respond to external risks, and thereby enhance economic resilience.

Hypothesis H1: Policy-based insurance for the three major staple grains significantly improves agricultural economic resilience.

3.2.2. Mediating Effect of Agricultural Technological Innovation

Policy-based agricultural insurance promotes technological innovation and the large-scale application of new technologies. Agricultural technological innovation is characterized by high investment, high risk, and a long payback period. Moreover, innovations applied in production are vulnerable to natural disasters, diseases, and pests, which may lead to substantial losses in innovation investment. By compensating for production losses, policy-based agricultural insurance partially covers risks associated with the application of technological innovations.

Meanwhile, sustained capital investment is essential for agricultural technological innovation. However, funds held by agricultural producers are often allocated to short-term activities such as purchasing production materials and expanding planting areas, leaving limited capital for long-term research and development (R&D). The risk protection function of policy-based agricultural insurance reduces the incentive for precautionary savings. After purchasing insurance, producers do not need to retain large sums of funds for potential losses and can allocate more capital to technological R&D. Stable risk expectations also improve credit access, further filling the R&D funding gap. Increased capital investment directly boosts R&D and is ultimately reflected in the growth of agricultural invention patents.

Agricultural technological innovation effectively drives the improvement of agricultural economic resilience. Its core mechanism is to provide key support for stable development through technological empowerment and system optimization. The traditional rural industrial model is constrained by a singular structure, which not only leads to large output fluctuations under external shocks (e.g., natural disasters) but also results in slow industrial income growth due to the low income elasticity of demand for agricultural products [46]. To resolve this dilemma, Zhou et al. and Liang and Liu pointed out that agricultural technological innovation enhances the resilience of the agricultural economic system by optimizing production factor allocation, improving production efficiency, and strengthening industrial risk resistance [47,48].

Hypothesis H2: Agricultural technological innovation plays a mediating role in the impact of policy-based insurance for the three major staple grains on agricultural economic resilience.

3.2.3. Mediating Effect of Regional Industrial Structure Upgrading

Policy-based agricultural insurance reduces the risk aversion of agricultural producers through risk protection, factor allocation, and the promotion of scaled operation. It guides capital and labor to shift from traditional planting and breeding to high value-added agriculture, forestry, animal husbandry and fishery services, and stimulates demand for large-scale and professional agricultural services. This increases the share of service output in the total agricultural output value and drives the advanced transformation of the agricultural industrial structure from "traditional farming-dominated" to "integrated farming and services".

As a mediating variable, regional industrial structure upgrading enhances the risk resistance of the agricultural economic system by optimizing industrial structure, provides pathways for economic recovery, and strengthens adaptability and flexibility [49,50]. It diversifies production risks through professional services, improves transformation capacity by adapting to market and technological changes, and accelerates recovery via post-disaster support, ultimately promoting agricultural economic resilience. A complete transmission chain is thus formed: policy-based agricultural insurance facilitates the growth of agricultural service industries (i.e., regional industrial structure upgrading), thereby improving agricultural economic resilience.

Hypothesis H3: Regional industrial structure upgrading plays a mediating role in the impact of policy-based insurance for the three major staple crops on agricultural economic resilience.

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4. Methodology

4.1. Data Sources

This study uses a balanced panel dataset of 31 provinces in mainland China from 2012 to 2023. The data are obtained from the China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Insurance Yearbook, China Science and Technology Statistical Yearbook, and provincial statistical yearbooks. Missing values are supplemented by linear interpolation. All monetary variables are deflated to constant 2012 prices.

4.2. Variable Definitions and Measurement

4.2.1. Dependent Variable: Agricultural Economic Resilience (AER)

This study analyzes agricultural economic resilience under the Pressure-State-Response (PSR) model. Agricultural economic resilience is defined as the ability of the system to maintain stable operation, gradually return to normality, and achieve renewal and development through the coordination of internal and external factors when suffering from risk shocks. Referring to the basic principles of the PSR model, this study constructs an evaluation system of agricultural economic resilience from three dimensions:

Pressure layer(P), the economic risk pressure faced by the agricultural system.Pressure indicators reflect the external disturbances to the agricultural economic system during development, mainly including natural disasters such as floods, droughts, hurricanes, earthquakes, and land pollution, which impact agricultural production and threaten the normal operation of the system. Therefore, four indicators reflecting losses caused by natural disasters and environmental pressure are selected for the Pressure layer: affected crop area, number of sudden environmental events, pesticide application per unit sown area, and agricultural plastic film application per unit sown area [20,24].

State layer(S), the operational status of the system under disturbance.State indicators reflect the operational performance of the agricultural economic system under various pressures, which can reflect the system’s coping ability. Following the principles of comprehensiveness, scientificity, representativeness, and data availability, seven indicators are finally selected to measure the system’s performance under pressure: grain output, added value of the primary industry, per capita education years of rural residents, number of employees in the primary industry, per capita disposable income of rural residents, rural electricity consumption, and effective irrigated area [29,32].

Response layer(R), the response measures taken by the system to cope with risks [24]. Response indicators refer to various countermeasures and measures taken to cope with agricultural economic risks and reduce potential losses, with implementation subjects including society and the government. The Response layer mainly reflects the self-organizing recovery actions of multi-level subjects such as farmers and rural areas to cope with risks, reflecting the investment and comprehensive strength in regional agricultural economic resilience construction. Five indicators are selected: fund for agricultural science and technology activities, agricultural insurance benefit expenditure, total power of agricultural machinery, land management, and expenditure on agriculture, forestry, and water [34,36,39].

Based on the PSR model framework, this study constructs an evaluation index system from the three dimensions of Pressure, State, and Response, as shown in Table 1.

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Table 1. Evaluation Indicators of Agricultural Economic Resilience.

First-Class Indicators	Second-Class Indicators	Indicator Explanation
Pressure Layer	Affected crop area (1,000 ha)	Area of affected crops
	Number of sudden environmental events	Number of sudden environmental events
	Pesticide application per unit sown area (t/1,000 ha)	Pesticide application / crop sown area
	Agricultural plastic film application per unit sown area (t/1,000 ha)	Agricultural plastic film use / crop sown area
State Layer	Per capita education years of rural residents (year)	Education years = (Primary×6 + Junior high×9 + Senior high×12 + College and above×15) / rural population aged over 6
	Employees in the primary industry (10,000 persons)	Number of employees in the primary industry
	Grain output (10,000 tons)	Output of grain and cereals
	Added value of the primary industry (100 million yuan)	Added value of the primary industry
	Agricultural electricity consumption (100 million kWh)	Electricity consumption for agricultural use
	Per capita disposable income of rural residents (yuan)	Per capita disposable income of rural residents
	Effective irrigated area (1,000 ha)	Area of effective irrigation
Response Layer	Total power of agricultural machinery (10,000 kW)	Total power of agricultural machinery
	Land management (1,000 ha)	Sum of waterlogging area and soil erosion control area
	Fund for agricultural science and technology activities (1 million yuan)	Internal R&D expenditure × proportion of total output value of agriculture, forestry, animal husbandry and fishery in regional GDP
	Expenditure on agriculture, forestry and water (100 million yuan)	Expenditure on agriculture, forestry and water
	Agricultural insurance benefit expenditure (1 million yuan)	Benefit expenditure of agricultural insurance

Data sources: China Statistical Yearbook, China Rural Statistical Yearbook, China Science and Technology Statistical Yearbook.

This study adopts the entropy method under the indicator system framework to determine indicator weights, since the entropy method [24] yields more objective and reliable weight results. The calculation procedures are detailed in the following steps, as shown in Equations (1)–(8):

(1) Construct the initial data matrix of the evaluation system:

$$X = \{x_{kij}\}_{\{y\times m\times n\}} \tag{1}$$

where x_{kij} denotes the value of the j-th indicator of agricultural economic resilience for region i in year k; y, m, and n represent the maximum values of k, i, and j, respectively.

Given that secondary indicators differ in units and dimensions, data standardization is conducted to ensure comparability and consistency. The standardization formulas are as follows:

Positive indicators:

$$x'_{kij} = \frac{x_{kij} - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

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Negative indicators:

$$x'_{kij} = \frac{X_{\max} - x_{kij}}{X_{\max} - X_{\min}} \tag{3}$$

where x'_{kij} is the standardized value; X_{max} and X_{min} are the maximum and minimum values of the indicator, respectively.

(2) Calculate the proportion of the j-th indicator for region *i*:

$$p_{kij} = \frac{x'_{kij}}{\sum\sum_{ik} x'_{kij}} \tag{4}$$

(3) Calculate the entropy value and deviation degree of the j-th indicator:

Entropy value:

$$e_j = -K\sum\sum_{ik}(p_{kij} \ln p_{kij} x'_{kij}) \tag{5}$$

where: $K = 1/\ln(y \times m)$

Deviation degree:

$$d_j = 1 - e_j \tag{6}$$

(4) Calculate the weight of the j-th indicator:

$$w_j = \frac{d_j}{\sum_j d_j} \tag{7}$$

(5) Calculate the comprehensive score for region i in year k:

$$S_{ki} = \sum_j (w_j \times x'_{kij}) \tag{8}$$

where S_{ki} represents the agricultural economic resilience score of region i in year k; a higher score indicates a higher level of regional agricultural economic resilience.

Based on the indicator weights determined by the entropy method, the agricultural economic resilience values for China from 2012 to 2023 were calculated using the above approach. From a national perspective (as shown in Figure 1), China's agricultural economic resilience increased from 0.19 in 2012 to 0.55 in 2020 and further to 0.87 in 2023, showing a stable upward trend overall.

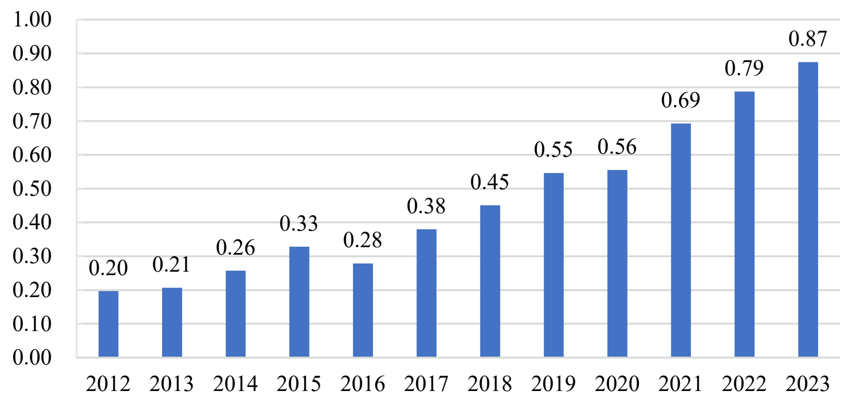

Figure 1. Calculation results of China's agricultural economic resilience from 2012 to 2023. Data source: Calculated by the authors using entropy method.

The measurement results of agricultural economic resilience in 31 provinces of China from 2012 to 2023 are presented in Appendix A, Table A1. At the provincial level, which presents the calculated agricultural economic resilience of China's 31 provinces from 2012 to 2023, provincial resilience shows a clear gradient and can be divided into three tiers (as shown in Table 2). The first tier consists of provinces with an average resilience value of 0.4–0.6; the second tier includes those with a value

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between 0.2 and 0.4; and the third tier covers provinces with a value below 0.2. The classification results based on the above criteria are shown in Table 2.

Table 2. Classification of Agricultural Economic Resilience Levels.

Tier	Provinces
Tier 1	Shandong, Henan, Jiangsu, Hebei, Heilongjiang, Sichuan
Tier 2	Guangdong, Anhui, Hunan, Hubei, Inner Mongolia, Xinjiang, Yunnan, Liaoning, Zhejiang, Guangxi, Jiangxi, Jilin, Shaanxi
Tier 3	Guizhou, Fujian, Gansu, Shanxi, Chongqing, Shanghai, Beijing, Ningxia, Tianjin, Hainan, Tibet, Qinghai

Based on the average agricultural economic resilience of China's 31 provinces from 2012 to 2023, Shandong Province has the highest mean value, followed by Henan and Jiangsu, all exceeding 0.5. With a diversified industrial structure and advanced agricultural industrialization, Shandong effectively disperses risks and enhances value-added, while also serving as a major agricultural province. Henan is China's core grain-producing region with the most stable output nationwide, ensuring steady agricultural production. Jiangsu ranks first in China in agricultural labor productivity and technological contribution rate. Driven by technological innovation and efficient agricultural transformation, it has diversified income sources, strengthened technological support for agriculture, and improved agricultural economic resilience.

For medium-level provinces represented by Anhui and Liaoning, possible reasons are as follows. Although Anhui is a major agricultural province, its industrial structure is relatively simple compared with Shandong, resulting in weaker risk-diversification capacity, and its technological innovation capability is lower than that of Jiangsu. Liaoning has resource advantages but, as an old industrial base, attaches less priority to agriculture and has a relatively weak agricultural foundation. Meanwhile, large-scale labor out-migration further constrains its resilience. Thus, its resilience level is higher than that of less developed western regions but still lags behind provinces such as Shandong and Henan.

The relatively low resilience in Beijing and Tianjin can be attributed to their status as municipalities whose economies are dominated by service and high-end manufacturing industries, with a small primary-industry labor force. Tibet and Qinghai show the lowest agricultural economic resilience, mainly due to harsh natural conditions such as high altitude and drought, which are unfavorable for crop growth, coupled with poor agricultural infrastructure and brain drain.

4.2.2. Core Independent Variable: DID

The core explanatory variable in this study is the policy variable (DID). Based on policy documents including the Pilot Work Plan for Full-Cost Insurance and Planting Income Insurance for Three Major Staple Crops and the Notice on Expanding the Implementation Scope of Full-Cost Insurance and Planting Income Insurance for Three Major Staple Crops, we identify the year in which each province approved and launched the pilot policy-based agricultural insurance for the three major staple crops.

Six provinces, namely Hubei, Anhui, Henan, Shandong, Liaoning, and Inner Mongolia, were approved for the pilot in 2018. Therefore, the policy variable DID for these provinces is assigned a value of 1 for 2018 and subsequent years, and 0 for years before 2018. Seven provinces, including Hebei, Jilin, Heilongjiang, Jiangsu, Jiangxi, Hunan, and Sichuan, were approved for the pilot in 2021, so the DID variable is set to 1 for 2021 and later years, and 0 for years prior to 2021. For provinces where the pilot had not been implemented by the end of 2023, the DID variable is assigned a value of 0 across all years.

4.2.3. Mediating Variables

The mediating variables in this study are as follows:

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(1) Agricultural Technological Innovation (ATI). Measurements of agricultural technological innovation generally fall into three categories: total agricultural R&D investment [51], the number of agricultural patents, and agricultural total factor productivity [52]. Following Lai et al. [53], this study uses the number of agricultural patents to measure agricultural technological innovation.

(2) Regional Industrial Structure Upgrading (RIS). Resource factors flow across industrial sectors through changes in technological proportion and technical efficiency, shifting from low-productivity sectors to high-productivity sectors, thereby achieving resource reallocation and a rising share of high-productivity sectors. Referring to Tang et al. [29], this study adopts the ratio of the output value of agriculture, forestry, animal husbandry and fishery services to the total output value of agriculture, forestry, animal husbandry and fishery as an indicator of agricultural industrial structure upgrading. A larger value indicates a higher level of agricultural industrial structure upgrading.

4.2.4. Control Variables

Regarding control variables, this study selects the following five indicators with reference to relevant studies on agricultural economic resilience by Hao and Tan [30], Zhao et al. [32], and others:

(1) Urbanization rate (town). Urbanization rate refers to the proportion of urban population in the total population. During urbanization, rural labor migrates to cities, which may pose challenges to agricultural production organizations in the short term. In the long run, however, urbanization promotes large-scale land transfer and the development of agricultural social services, helping to improve the scale and modernization of agricultural operations. Meanwhile, regions with higher urbanization rates usually have stronger financial support for agriculture, more complete agricultural infrastructure, and a more sound agricultural insurance system, which are conducive to agricultural stability [32].

(2) Industrialization level (industry). Industrialization level refers to the degree of industrial development in a country or region, measured by industrial added value in this study. With the improvement of industrialization, first, the shares of industry and services in the industrial structure rise while the agricultural share declines. Second, agricultural labor shifts to non-agricultural sectors at the labor allocation level, which may lead to rural labor shortages and further affect agricultural production and economic stability [35].

(3) Total retail sales of consumer goods (TRSCG). Measured as the ratio of total retail sales of consumer goods to regional GDP, it reflects the scale and structure of regional consumer demand. Excessive expansion of the consumer market may cause production factors to concentrate in non-agricultural sectors, reducing resources allocated to agriculture [36].

(4) Regional per capita GDP (lnGDP). The natural logarithm of per capita GDP at the provincial or municipal level [12].

(5) Road network density (RD). Calculated as the total mileage of highways and railways divided by administrative area. Infrastructure such as highways provides important conditions for agricultural mechanization and exerts a significant influence on the resilience of agricultural economic recovery [54].

4.2.5. Descriptive Statistics

Table 3 reports the descriptive statistics of the main variables used in this study. The mean value of agricultural economic resilience (AER) is 0.263, with a minimum of 0.033 and a maximum of 0.683, indicating substantial regional disparities in resilience across China. The mean of the DID variable is 0.153, consistent with the phased implementation of the staple crop insurance policy. The mediating variables—agricultural technological innovation (ATI) and regional industrial structure upgrading (RIS)—also display considerable variation, suggesting potential differences in technological progress and structural transformation across provinces. Control variables, including urbanization rate, industrialization level, social consumption level, regional per capita GDP, and road network density, are within reasonable ranges and show no extreme outliers.

Table 3. Variable Definitions and Descriptive Statistics of main variables (2012-2023).

Variable Category	Variable Name	Variable Definition	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable	AER	Agricultural Economic Resilience	372	0.263	0.151	0.033	0.683
Independent Variable	DID	Policy Variable	372	0.153	0.361	0.000	1.000
Mediating Variables	ATI	Agricultural Technological Innovation (thousands)	372	3.221	3.196	0.011	16.651
	RIS	Regional Industrial Structure Upgrading	372	0.043	0.019	0.002	0.096
Control Variables	town	Urbanization Rate (%)	372	60.272	12.619	22.750	89.600
	industry	Industrialization Level (trillion yuan)	372	1.013	0.937	0.006	4.924
	TRSCG	Total retail sales of consumer goods	372	0.379	0.070	0.183	0.538
	lnGDP	Regional Per Capita GDP (log)	372	10.965	0.445	9.889	12.207
	RD	Road Network Density (%)	372	0.980	0.547	0.055	2.309

Data source: Calculated and organized using Stata 18 based on the collected and processed data.

4.3. Econometric Models

4.3.1. Baseline Model

To investigate the impact of policy-based agricultural insurance on agricultural economic resilience, this study constructs a difference-in-differences (DID) model for policy effect evaluation by referring to relevant literature [12], as shown in Equation (9):

$$AER_{it} = \alpha_0 + \alpha_1 DID_{it} + X'_{it}\gamma + \mu_t + \lambda_i + \varepsilon_{it} \tag{9}$$

Where the subscript i denotes provinces and t denotes years.

The dependent variable AER_{it} measures the agricultural economic resilience of province i in year t. The core explanatory variable is the policy interaction term DID_{it}, specifically defined as $DID_i = treat_i \times post_t$. Here, $treat_i$ is a group dummy variable: $treat_i$=1 if province i is a pilot province, and $treat_i$=0 otherwise. $post_t$ is a time dummy variable: $post_t$=0 for years before the pilot launch, and $post_t$=1 for the pilot year and subsequent years.

X'_{it} represents control variables; λ_i is the provincial fixed effect; μ_t is the time fixed effect; ϵ_{it} is the error term; α_0 is the intercept; α_1 is the estimated coefficient of the core explanatory variable, namely the DID estimator, which reflects the magnitude and direction of the impact of China's policy-based agricultural insurance pilot for the three major staple crops on agricultural economic resilience; γ is the estimated coefficient of the control variables.

4.3.2. Mediating Effect Models

This study adopts the mediating effect test method proposed by Wen and Ye [55] and uses agricultural technological innovation and agricultural industrial structure upgrading as mediating variables to examine the mediating mechanism. Based on Equation (9), the following mediating effect models are constructed for mechanism analysis (see Equations (10) and (11)):

$$Med_{it} = \rho_0 + \rho_1 DID_{it} + X'_{it}\gamma + \mu_t + \lambda_i + \varepsilon_{it} \tag{10}$$

$$AER_{it} = \pi_0 + \pi_1 DID_{it} + \pi_2 bzmj_{it} + X'_{it}\gamma + \mu_t + \lambda_i + \varepsilon_{it} \tag{11}$$

In Equations (9), (10), and (11), the dependent variable AER_{it} denotes agricultural economic resilience of province i in year t; DID_{it} is the policy interaction term; Med_{it} represents each mechanism variable; X'_{it} denotes control variables; γ, ρ_0, and ρ_1 are parameters to be estimated; λ_i is the provincial fixed effect; μ_t is the time fixed effect; and ϵ_{it} is the error term.

We focus on the coefficients $\alpha 1$, ρ_1, and π_2. If α_1 is statistically significant and both the indirect effect coefficient ρ_1 and direct effect coefficient π_2 are significant, this indicates that agricultural technological innovation and agricultural industrial structure upgrading play mediating roles in the impact of policy-based agricultural insurance on agricultural economic resilience.

4.3.3. Heterogeneity Analysis Model

The heterogeneity model is constructed as shown in Equation (12). Models for heterogeneous effects across regions, staple grain production levels, and natural risk levels follow the same specification as the benchmark regression model, differing only in sample scope.

$$AER_{it} = \beta_0 + \beta_1 DID_{it} + X'_{it}\beta + \mu_t + \lambda_i + \varepsilon_{it} \quad (12)$$

5. Empirical Results

5.1. Baseline Regression Results

Table 4 presents the baseline estimation results using the multi-timepoint DID model. Columns (1)–(4) gradually add control variables and fixed effects. The baseline regression results show that in Model (1), without control variables and fixed effects, the DID coefficient is 0.2075 and significant at the 1% level. In Model (2), with control variables added, the coefficient decreases to 0.1578 and remains significant at the 1% level. In Models (3) (only two-way fixed effects) and (4) (full model), the DID coefficients are 0.0248 and 0.0251 respectively, both significant at the 1% level. After including all control variables and controlling for two-way fixed effects, agricultural economic resilience in pilot provinces increases by approximately 2.48%–2.51% compared with non-pilot provinces, verifying Hypothesis H1. The result shows that policy-based agricultural insurance exerts a significant positive promoting effect on agricultural economic resilience.

Table 4. Baseline regression results of the impact of policy-based insurance on AER.

Variables	(1)	(2)	(3)	(4)
DID	0.2075***	0.1578***	0.0248***	0.0251***
	(0.03492)	(0.02659)	(0.00465)	(0.00470)
town		-0.0009		0.0040***
		(0.00329)		(0.00082)
industry		0.1157***		0.0018
		(0.02062)		(0.00562)
TRSCG		-0.0879		-0.0392
		(0.18879)		(0.03591)
lnGDP		-0.0950		0.0142
		(0.08065)		(0.01443)
RD		0.0179		0.0053
		(0.04268)		(0.01737)
_cons	0.2312***	1.2332*	0.2135***	-0.1416
	(0.02340)	(0.69468)	(0.00397)	(0.14087)
Control variables	No	Yes	No	Yes
Province fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Observations	372	372	372	372
R-squared	0.244	0.666	0.734	0.758

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

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Among the control variables, the urbanization rate shows a significantly positive effect at the 1% level. The increase in urbanization rate significantly promotes agricultural economic resilience, possibly because urbanization improves infrastructure, upgrades public services, and perfects market mechanisms, thereby providing a more favorable environment for agricultural development and strengthening agricultural economic resilience. The industrialization level is significantly positive when time and individual fixed effects are not included, but becomes insignificant after controlling for both. This may be due to the high correlation between industrialization and inherent provincial characteristics as well as macro time trends, leaving insufficient residual variation to identify its independent effect.

The coefficient of social consumption level is statistically insignificant. Higher social consumption may divert more resources to non-agricultural sectors and squeeze agricultural production to a certain extent; however, policy-based agricultural insurance and fiscal support for agriculture have mitigated such negative impacts. The coefficient of regional per capita GDP is also insignificant. On the one hand, regional economic development can enhance agricultural economic resilience through fiscal support for agriculture and improved infrastructure. On the other hand, economic development may be accompanied by rising production costs, leading to an insignificant net effect. Road network density is insignificant as well. Improved transportation reduces logistics costs and facilitates factor mobility, which strengthens agricultural resilience. Meanwhile, road expansion may accelerate rural labor outflows and raise land rents, exerting adverse effects on agriculture. The two opposing effects offset each other, resulting in an overall insignificant impact.

5.2. Robustness Tests

5.2.1. Parallel Trend Test

The validity of the difference-in-differences method relies on the parallel trends assumption, namely that agricultural economic resilience in pilot and non-pilot provinces exhibited no significant differences prior to the launch of the policy-based insurance pilot for the three major staple crops. Following the event study approach proposed by McGavock [56], as well as the empirical methods of Beck et al. [57] and Tang Haodan [58], this study takes period −1 as the base period, aggregates policy effects for the five years before the pilot, and examines the dynamic effects of the policy on regional agricultural economic resilience before and after implementation.

The test results shown in Figure 2 indicate that no significant differences existed between the treatment and control groups before the implementation of the policy-based agricultural insurance pilot for the three major staple crops, satisfying the parallel trends assumption and providing a reasonable basis for the application of the DID method. From the perspective of ex-post dynamic effects, the promoting effect of the pilot policy on agricultural economic resilience became evident in the second year after the launch of the pilot. In summary, the promotion of the policy-based agricultural insurance pilot for the three major staple crops can effectively support the improvement of agricultural economic resilience, although its effect exhibits a certain time lag.

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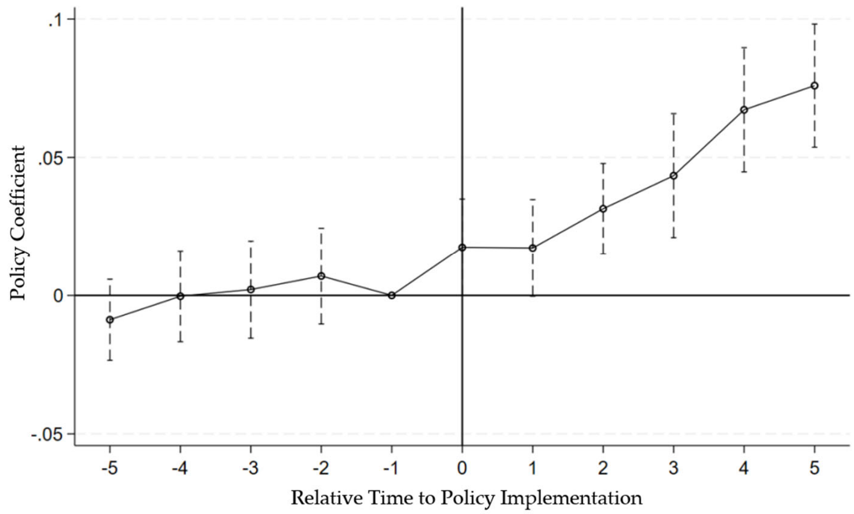

Figure 2. Dynamic Effect of Policy-Based Agricultural Insurance on Agricultural Economic Resilience.

5.2.2. Placebo Test

To verify that the impact of the policy-based agricultural insurance pilot for the three major staple crops on agricultural economic resilience is not caused by random chance, this study employs a placebo test to identify the randomness of the policy effect. Following the empirical methods of La Ferrara et al. [59] and Hu Jie [60], a pseudo-policy variable is constructed through 1,000 random samplings and substituted into Model (9) for re-regression.

As shown in Figure 3, the regression coefficients corresponding to the pseudo-policy variable constructed by random sampling are mostly concentrated around zero. The mean value of these coefficients is much lower than the real estimate obtained in the baseline regression, and their overall distribution approximates a normal distribution. In terms of statistical significance, the p-values corresponding to the estimated coefficients of most pseudo-policy variables are greater than 0.10, implying that these fictitious treatment effects are insignificant at the 10% significance level.

This test confirms the robustness of the baseline regression, indicating that the promoting effect of the pilot policy on agricultural economic resilience does not stem from unobservable factors or random errors, thereby further enhancing the credibility of the research conclusions.

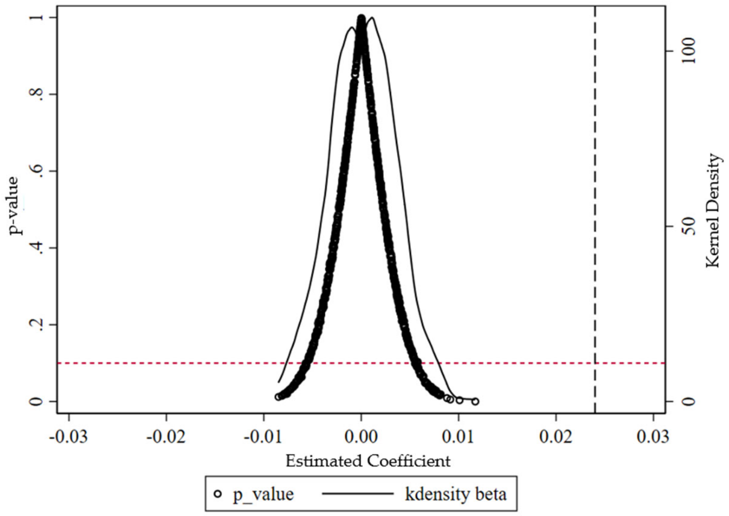

Figure 3. Coefficient Distribution from the Placebo Test.

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5.2.3. Exclusion of Municipalities Directly Under the Central Government

Considering the distinctive economic characteristics of municipalities directly under the central government in China, this study excludes the samples of Beijing, Tianjin, Shanghai and Chongqing to eliminate their potential influence on the estimation results, and re-runs the regression based on the data of the remaining 27 provinces. As shown in Column (4) of Table 5, the estimated coefficient is still significantly positive at the 1% statistical level, indicating that the research conclusion is highly robust.

Table 5. Robustness test: excluding municipalities directly under the central government.

Variables	(1)	(2)	(3)	(4)
DID	0.1853***	0.1419***	0.0170***	0.0195***
	(0.03493)	(0.03070)	(0.00456)	(0.00491)
town		0.0002		0.0008
		(0.00359)		(0.00156)
industry		0.0997***		-0.0051
		(0.02694)		(0.00625)
TRSCG		-0.1712		-0.0133
		(0.24428)		(0.03889)
lnGDP		-0.0982		0.0262
		(0.08380)		(0.01815)
RD		0.0546		0.0025
		(0.05699)		(0.02345)
_cons	0.2533***	1.2308*	0.2340***	-0.0742
	(0.02530)	(0.71636)	(0.00402)	(0.15302)
Control variables	No	Yes	No	Yes
Province fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Observations	324	324	324	324
R^2	0.227	0.628	0.785	0.789

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

5.2.4. Excluding Interference from Other Policies

To eliminate the interference of other potential policies that may affect agricultural economic resilience, this paper excludes the interference of soybean-related policies.

In July 2017, the *Notice on Adjusting and Improving the Corn and Soybean Subsidy Policy* (Cai Nong [2017] No. 84) launched subsidy pilots in Inner Mongolia, Liaoning, Heilongjiang and Jilin, which was further refined in July 2020. As corn and soybeans share a unified subsidy mechanism and soybeans compete directly with major staple crops, farmers adjust planting decisions based on subsidy incentives. Such behavioral changes may bias the estimated effect of policy-based agricultural insurance for the three major staples. Following Qiu et al. [61] and Gong and Wu [62], we adopt two strategies to mitigate this bias: controlling for the subsidy policy and excluding pilot provinces from the sample.

First, the dummy variable DID1 for the 2017 corn and soybean producer subsidy policy is added to Equation (9). If the core estimation coefficient of policy-based agricultural insurance for the three major staple crops is no longer significant after introducing the new variable, it indicates that the baseline regression results may be confounded by concurrent policies and their robustness is questionable. Conversely, if the policy effect remains significant, it proves the robustness of the results. After adding the dummy variable to the baseline model, the regression results are shown in Column (1) of Table 6. The regression coefficient of the pilot policy for policy-based insurance for the three major staple crops remains significantly positive, indicating that even after considering the impact of the corn and soybean producer subsidy policy, the effect of policy-based insurance on agricultural economic resilience is still robust. This verifies the robustness of the regression results in this paper.

Second, the corn and soybean producer subsidy policy was implemented in 2017, with Inner Mongolia, Liaoning, Heilongjiang and Jilin as the pilot regions. Referring to the empirical method of Zhang et al. [63], the samples of pilot provinces for the corn and soybean producer subsidy policy are excluded for re-regression analysis. The regression results shown in Column (2) of Table 6 indicate that the regression coefficient of the pilot policy for policy-based insurance for the three major staple crops remains significantly positive, verifying the reliability of the conclusions of this paper.

5.2.5. Shortening the Sample Period

Considering that the policy-based agricultural insurance pilot for the three major staple crops was launched in 2018, the baseline sample period of this study is set from 2012 to 2023. To eliminate the interference of the COVID-19 pandemic, a major public emergency, on agricultural production and ensure the reliability of the core conclusions, samples from the pandemic period (2020–2022) are excluded for robustness testing. As shown in Column (3) of Table 6, the coefficient of the core explanatory variable remains significantly positive. This indicates that the enhancing effect of policy-based agricultural insurance for the three major staple crops on agricultural economic resilience still holds after excluding the pandemic disturbance, confirming the strong robustness of the baseline regression results.

Table 6. Regression Results Considering the Influence of Concurrent Interfering Policies.

Variables	**(1) Adding Policy Dummy Variables**	**(2) Excluding Partial Samples**	**(3) Shortening the Sample Period**
DID	0.0217***	0.0266***	0.0261***
	(0.00484)	(0.00542)	(0.00583)
DID1	0.0223**		
	(0.00862)		
Town	0.00405***	0.00374***	0.00280***
	(0.000813)	(0.000843)	(0.000915)
Industry	0.00410	0.00312	0.0120*
	(0.00565)	(0.00579)	(0.00677)
TRSCG	-0.0247	-0.0342	-0.0178
	(0.0360)	(0.0456)	(0.0358)
lnGDP	0.0322**	0.0304*	0.00320
	(0.0159)	(0.0172)	(0.0166)
RD	0.00560	0.0140	-0.000957
	(0.0172)	(0.0179)	(0.0210)
_cons	-0.343**	-0.314*	0.0275
	(0.160)	(0.174)	(0.162)
Control variables	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	372	324	279
R^2	0.763	0.754	0.769

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

5.3. Mechanism Analysis: Mediating Effects

The above analysis has examined the impact of the policy-based agricultural insurance for the three major staple crops on agricultural economic resilience. The following section further explores the underlying mechanism by investigating the mediating effects of agricultural technological innovation (ATI) and regional industrial structure upgrading (RIS). Drawing on the mediating effect test method proposed by Wen Zhonglin and Ye Baojuan [55], this study empirically examines the mediating roles of agricultural technological innovation and agricultural industrial structure upgrading in the process through which policy-based agricultural insurance affects agricultural economic resilience.

5.3.1. Mediating Effect Test of Agricultural Technological Innovation

This study constructs an analytical model with agricultural technological innovation as the mediating variable and conducts regression analysis using Equation (12). Table 7 reports the results of the mediating role of agricultural technological innovation in the relationship between policy-based agricultural insurance for the three major staple crops and agricultural economic resilience.

Column (1) of Table 7 shows that the policy has a significant positive impact on agricultural economic resilience. Column (2) indicates that the regression coefficient of the policy on agricultural technological innovation is 0.594, which is statistically significant at the 5% level, suggesting that agricultural technological innovation is a key channel through which the policy affects agricultural economic resilience.

All coefficients in Table 7 pass the significance test, and the Bootstrap confidence intervals exclude zero, confirming the mediating effect. These findings demonstrates that agricultural technological innovation exerts a mediating effect in the process whereby policy-based agricultural insurance promotes the improvement of agricultural economic resilience. This is consistent with the findings of Yang et al. [64] and Li and Wan [39], thus verifying that Research Hypothesis H2 of this paper holds true.

Table 7. Mediating effect test results of agricultural technological innovation.

Variables	(1)	(2)	(3)
DID	0.0251***	0.594**	0.0223***
	(0.00470)	(0.239)	(0.00461)
ATI			0.00476***
			(0.00106)
Town	0.00399***	-0.0325	0.00414***
	(0.000820)	(0.0416)	(0.000797)
Industry	0.00176	3.052***	-0.0128**
	(0.00562)	(0.285)	(0.00636)
TRSCG	-0.0392	3.461*	-0.0556
	(0.0359)	(1.822)	(0.0351)
lnGDP	0.0142	-1.740**	0.0224
	(0.0144)	(0.732)	(0.0141)
RD	0.00529	0.601	0.00243
	(0.0174)	(0.881)	(0.0169)
_cons	-0.142	17.02**	-0.223
	(0.141)	(7.146)	(0.138)
Control Variables	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Bootstrap: 95% Confidence Interval		（0.000,0.006）	

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Observations	372	372	372
R^2	0.758	0.660	0.772

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

5.3.2. Mediating Effect Test of Regional Industrial Structure Upgrading

Table 8 presents the results of the mediating role of regional industrial structure upgrading in the relationship between policy-based agricultural insurance for the three major staple crops and agricultural economic resilience. Column (1) of Table 8 shows that the policy has a significant positive impact on agricultural economic resilience. Column (2) indicates that the effect of the policy on regional industrial structure upgrading is significant at the 1% level, with a regression coefficient of 0.008, suggesting that regional industrial structure upgrading is a transmission path through which the policy affects agricultural economic resilience.

All coefficients in Table 8 pass the significance test, and the Bootstrap confidence interval exclude zero, confirming the mediating effect. The above analysis demonstrates that the upgrading of agricultural industrial structure exerts a mediating effect in the process whereby policy-based agricultural insurance promotes the improvement of agricultural economic resilience. This is consistent with the findings of Tang and Chen [29] and Li et al. [65], thus verifying that Research Hypothesis H3 of this paper holds true.

Table 8. Mediating effect test results of regional industrial structure upgrading.

Variables	**(1)**	**(2)**	**(3)**
DID	0.0251***	0.00843***	0.0202***
	(0.00470)	(0.00160)	(0.00481)
RIS			0.590***
			(0.160)
Town	0.00399***	-0.000769***	0.00444***
	(0.000820)	(0.000280)	(0.000814)
Industry	0.00176	0.00734***	-0.00257
	(0.00562)	(0.00192)	(0.00564)
TRSCG	-0.0392	0.0172	-0.0493
	(0.0359)	(0.0122)	(0.0353)
lnGDP	0.0142	-0.00119	0.0149
	(0.0144)	(0.00492)	(0.0142)
RD	0.00529	0.0101*	-0.000693
	(0.0174)	(0.00592)	(0.0171)
_cons	-0.142	0.0661	-0.181
	(0.141)	(0.0480)	(0.139)
Control Variables	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Bootstrap: 95% Confidence Interval		(0.001,0.009)	
Observations	372	372	372
R^2	0.758	0.476	0.768

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

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5.4. Heterogeneity Analysis

5.4.1. Heterogeneity Analysis Across Different Regions

Based on geographical differences, the full sample is divided into eastern, central, and western regions for grouped regression analysis. The corresponding results are presented in Columns (1), (2), and (3) of Table 11.

The empirical results reveal obvious regional heterogeneity. In the western region, policy-based agricultural insurance for the three major staple crops significantly improves agricultural economic resilience at the 1% level. In the central region, such insurance exerts a significantly positive effect at the 10% significance level. By contrast, no significant effect is observed in the eastern region.

The underlying reasons are as follows. Compared with the western region, the eastern and central regions feature higher living standards, diversified agricultural structures, and abundant production resources. These regions are less vulnerable to natural disasters and market fluctuations, which weakens the marginal improvement effect of agricultural insurance. Furthermore, with a higher level of economic development, farmers in eastern regions have better risk awareness and can adopt alternative risk management tools, thereby limiting the protective role of agricultural insurance.

In the western region with scarce agricultural resources, frequent natural disasters and underdeveloped markets, agricultural insurance serves as the core risk protection instrument. It effectively stabilizes agricultural production, mitigates shocks from natural disasters and market volatility, and generates a more pronounced enhancement effect on agricultural economic resilience.

5.4.2. Heterogeneity Analysis by Different Staple Grain Production Levels

Given China's vast territory and distinct regional characteristics, agricultural economic development and major grain production conditions vary across regions. When facing identical external shocks, the policy effects on enhancing agricultural economic resilience also differ. This study divides sample provinces into major staple grain-producing provinces (the top 50% by the share of cereal output in total grain output) and non-major staple grain-producing provinces (the remaining 50%). This classification allows for further analysis of the heterogeneous impact of the three major staple crops policy-based agricultural insurance on agricultural economic resilience. The classification criteria for the two groups are presented in Table 9.

Table 9. Classification of Major and Non-Major Staple Grain Producing Provinces.

Classification	Provinces
Major staple grain producing provinces	Liaoning, Xinjiang, Jilin, Shanghai, Tianjin, Xizang, Jiangsu, Anhui, Shandong, Henan, Hunan, Hubei, Shanxi, Jiangxi, Beijing, Hebei
Non-major staple grain producing provinces	Guangxi, Ningxia, Guangdong, Inner Mongolia, Zhejiang, Shaanxi, Heilongjiang, Hainan, Yunnan, Sichuan, Fujian, Gansu, Qinghai, Guizhou, Chongqing

Note: Classification is based on the share of cereal output in total grain output. Heilongjiang is classified as a non-major province due to its high soybean production share.

Columns (4) and (5) in Table 11 report the heterogeneous effects of the policy on major and non-major staple grain-producing provinces, respectively. The results show that the policy-based agricultural insurance pilot has a significant positive impact on agricultural economic resilience in non-major staple grain-producing provinces, while no significant effect is observed in major staple grain-producing provinces.

This difference may stem from the varying stages of agricultural insurance development in the two types of regions. Major staple grain-producing provinces have long benefited from preferential national policies, having established multi-level protection systems such as catastrophe insurance

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prior to the pilot, with well-developed agricultural infrastructure and mature risk management systems. As a result, there is limited room for marginal improvement from the new insurance policy. In contrast, farmers in non-major staple grain-producing provinces face higher risks with fewer effective hedging tools, as their insurance coverage is generally lower. The pilot policy thus provides substantial protection to these farmers. Beyond post-disaster compensation, insurance stabilizes income expectations and encourages farmers to invest in new technologies, thereby significantly enhancing agricultural economic resilience.

5.4.3. Heterogeneity Analysis Across Different Natural Risk Levels

The policy-based agricultural insurance for the three major staple crops aims to provide farmers with more comprehensive risk protection and enhance the stability of the agricultural economic system. In regions with high natural risk levels, the pilot policy can more effectively mitigate the adverse impacts of risk events, thereby exerting a more pronounced effect on improving agricultural economic resilience.

Accordingly, this study classifies natural risk levels across regions in China based on both productivity and natural risk, following the method proposed by Liang Laicun [66]. The natural risk level is measured by constructing an indicator system from two dimensions: yield per unit area and planting area, which covers both productivity and natural risk factors. Cluster analysis is then applied to assess the degree to which natural risks affect food security across regions in China. The sample regions are then grouped by the obtained natural risk levels for subgroup regression analysis, as shown in Table 10.

Table 10. Distribution of the Degree of Natural Risk Impact on Food Security by Province.

Risk Level	Provinces
Low Natural Risk Zone	Liaoning, Jilin, Jiangsu, Guangxi, Chongqing, Xinjiang, Jiangxi, Hunan, Sichuan, Beijing, Shanghai, Zhejiang, Fujian, Guangdong
Medium-High Natural Risk Zone	Anhui, Shandong, Henan, Hubei, Tianjin, Hebei, Inner Mongolia, Heilongjiang, Shanxi, Shaanxi, Gansu, Qinghai, Ningxia, Yunnan, Guizhou, Hainan, Xizang

Note: The classification criteria for natural risk levels refer to Liang Laicun [66].

Columns (6) and (7) in Table 11 report the heterogeneous effects of the policy on low natural risk zone and medium-high natural risk zone, respectively. Empirical findings show that the pilot policy exerts a significant positive impact on agricultural economic resilience in medium-high natural risk zones, while no significant effect is observed in low natural risk zones. This indicates that policy-based agricultural insurance can effectively enhance the resilience of the agricultural economy in regions with higher natural risks.

The underlying reason may be that farmers in high natural risk zones face greater risks and thus have a stronger demand for risk protection. As an effective risk protection instrument, policy-based agricultural insurance is more likely to be adopted by farmers in high-risk zones. Moreover, insurance payouts can effectively mitigate losses caused by natural disasters and other risks, thereby significantly strengthening agricultural economic resilience in these regions. In contrast, farmers in low natural risk zones face fewer risks and have lower demand for risk protection. Consequently, the policy-based agricultural insurance for the three major staple crops has no significant impact on agricultural economic resilience in low natural risk zones.

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Table 11. Heterogeneity Analysis by Region, Staple Grain Production Level and Natural Risk Level.

Variables	(1) Eastern Region	(2) Central Region	(3) Western Region	(4) Major Staple Grain Producing Provinces	(5) Non-Major Staple Grain Producing Provinces	(6) Low Natural Risk Zone	(7) Medium-High Natural Risk Zone
DID	-0.00173	0.0141*	0.0418***	0.00187	0.0395***	0.00484	0.0355***
	(0.00918)	(0.00743)	(0.0138)	(0.00617)	(0.00803)	(0.00825)	(0.00520)
Town	0.00256	0.00395	-0.00229	0.00160	0.00352***	0.00851***	0.00132
	(0.00158)	(0.00341)	(0.00255)	(0.00192)	(0.000828)	(0.00119)	(0.00122)
Industry	0.0156*	-0.00718	0.107***	-0.0137*	-0.000126	-0.0124*	0.0294**
	(0.00841)	(0.0305)	(0.0260)	(0.00753)	(0.0112)	(0.00701)	(0.0134)
TRSCG	0.0380	0.0256	-0.111	-0.00658	-0.119**	-0.0886	0.0486
	(0.0708)	(0.0485)	(0.0799)	(0.0494)	(0.0468)	(0.0629)	(0.0373)
lnGDP	-0.00968	-0.0335	0.0118	0.0349	0.0159	0.0540**	-0.0227
	(0.0265)	(0.0469)	(0.0271)	(0.0242)	(0.0190)	(0.0227)	(0.0189)
RD	0.0640	0.0133	-0.0162	-0.000946	0.00327	-0.0613**	0.0247
	(0.0425)	(0.0337)	(0.0231)	(0.0355)	(0.0185)	(0.0266)	(0.0225)
_cons	0.0778	0.448	0.187	-0.0788	-0.196	-0.771***	0.362**
	(0.315)	(0.419)	(0.294)	(0.202)	(0.202)	(0.248)	(0.173)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132	120	120	180	192	168	204
R^2	0.988	0.983	0.984	0.978	0.963	0.973	0.992

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

6. Discussion

This study investigates the causal impact of policy-based insurance for three major staple crops on agricultural economic resilience using a multi-timepoint DID model. The baseline results show that the policy significantly improves resilience, which is robust to a series of rigorous tests. The findings are consistent with recent studies emphasizing that policy-supported agricultural insurance stabilizes production, reduces vulnerability, and supports sustainable agricultural development. Specifically, our results align with global empirical evidence showing that agricultural insurance enhances agricultural resilience by mitigating farmers' risk aversion and encouraging investment in productivity-enhancing technologies [37].

Our mechanism analysis reveals two novel pathways: agricultural technological innovation and regional industrial structure upgrading. By reducing downside risk, insurance encourages

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investment in technology and structural transformation, which are essential for long-term resilience. This finding extends the literature by moving beyond short-term income or output effects to focus on sustainable capacity building.

Heterogeneity analysis shows that the policy is more effective in central and western regions, non-major grain-producing provinces, and medium-to-high natural risk zones. This pattern reflects the policy's role as a safety net for regions with weaker risk resistance and less developed agricultural systems. Such differentiated effects highlight the importance of targeted and region-specific policy design.

Compared with existing studies, this study provides more reliable causal evidence and clarifies the internal mechanism of resilience improvement. The results contribute to the global understanding of how public policy can strengthen agricultural sustainability and food security under increasing uncertainty.

However, some limitations should be acknowledged. First, this study uses provincial-level data; future research can use county-level or micro-farm data for more detailed analysis. Second, we focus on internal mechanisms; spatial spillover effects can be explored in future studies.

7. Conclusions and Policy Recommendations

7.1. Main Conclusions

Based on panel data from 31 Chinese provinces covering 2012–2023, this study employs a multi-timepoint DID model to estimate the impacts of policy-based insurance for the three major staple crops on agricultural economic resilience (AER). The main conclusions are as follows:

(1) Policy-based insurance for the three major staple crops presents a significant positive effect on AER, and the improvement effect is notably stronger in pilot regions than in non-pilot regions.

(2) Heterogeneity results show that the policy exerts a more pronounced boosting effect on AER in central and western regions, non-major staple grain-producing provinces, and medium-high natural risk zones, with the strongest effect observed in the western region.

(3) Mechanism tests verify that policy-based insurance for the three major staple crops enhances AER through two mediating pathways: agricultural technological innovation and regional industrial structure upgrading.

7.2. Policy Recommendations

To strengthen the role of policy-based insurance for the three major staple crops in improving AER and support high-quality agricultural development, this study proposes the following recommendations:

(1) Optimize the agricultural industrial structure by diversifying planting and breeding industries, extending the agricultural industrial chain, and supporting new-type agricultural operators with preferential premium subsidies to diversify operational risks and strengthen the industrial foundation for resilience.

(2) Improve the design of policy-based agricultural insurance products by expanding coverage from staple grains to cash crops and carrying out refined risk zoning at the county and township levels to develop customized insurance products that match regional risk characteristics.

(3) Implement differentiated financial subsidy policies by increasing premium subsidies for western provinces and high natural-risk regions, and develop targeted insurance products for non-major staple grain-producing provinces to meet diversified risk protection needs. Establish a dynamic adjustment mechanism for subsidy ratios based on annual disaster losses and local fiscal capacity.

(4) Strengthen the R&D and application of advanced agricultural technologies by introducing professional talents, increasing R&D investment, improving the technology extension system, and incentivizing farmers to adopt new technologies through appropriate premium discounts.

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Abbreviations

The following abbreviations are used in this manuscript:

AER	Agricultural Economic Resilience
DID	Difference-in-Differences
ATI	Agricultural Technological Innovation
RIS	Regional Industrial Structure Upgrading
PSR	Pressure-State-Response

Appendix A

The following tables provide full analytical outputs supplementing the results re-ported in Section 4.2.1. The appendix table are cited in the main text at the relevant point of discussion.

Table A1. Measurement Results of Agricultural Economic Resilience in 31 Provinces of China (2012–2023).

Province	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Average**
Shandong	0.519	0.533	0.539	0.558	0.539	0.567	0.570	0.566	0.583	0.623	0.647	0.683	0.577
Henan	0.458	0.465	0.471	0.485	0.477	0.498	0.513	0.539	0.564	0.596	0.643	0.669	0.532
Jiangsu	0.459	0.480	0.495	0.512	0.525	0.529	0.548	0.572	0.597	0.498	0.517	0.547	0.523
Hebei	0.405	0.413	0.420	0.436	0.408	0.412	0.416	0.431	0.452	0.464	0.486	0.533	0.440
Heilongjiang	0.323	0.374	0.364	0.380	0.407	0.422	0.425	0.481	0.474	0.486	0.486	0.516	0.428
Sichuan	0.324	0.339	0.352	0.372	0.382	0.399	0.423	0.445	0.471	0.499	0.512	0.536	0.421
Guangdong	0.317	0.326	0.335	0.352	0.355	0.370	0.388	0.415	0.442	0.405	0.440	0.500	0.387
Anhui	0.305	0.325	0.331	0.342	0.368	0.370	0.381	0.394	0.417	0.424	0.469	0.475	0.383

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Hunan	0.295	0.308	0.320	0.331	0.342	0.350	0.359	0.386	0.396	0.425	0.443	0.469	0.369
Hubei	0.275	0.292	0.302	0.313	0.319	0.329	0.342	0.356	0.370	0.394	0.424	0.449	0.347
Inner Mongolia	0.243	0.256	0.263	0.275	0.276	0.321	0.311	0.317	0.334	0.352	0.397	0.429	0.315
Xinjiang	0.181	0.206	0.225	0.234	0.246	0.242	0.225	0.303	0.325	0.340	0.359	0.420	0.276
Yunnan	0.213	0.227	0.237	0.242	0.254	0.257	0.266	0.286	0.304	0.315	0.328	0.335	0.272
Liaoning	0.243	0.242	0.250	0.260	0.252	0.263	0.247	0.258	0.269	0.277	0.304	0.320	0.265
Zhejiang	0.224	0.238	0.243	0.253	0.259	0.263	0.271	0.284	0.289	0.254	0.271	0.288	0.261
Guangxi	0.195	0.201	0.210	0.215	0.220	0.224	0.230	0.253	0.256	0.283	0.322	0.319	0.244
Jiangxi	0.201	0.191	0.198	0.204	0.210	0.215	0.220	0.230	0.246	0.258	0.283	0.300	0.230
Jilin	0.190	0.190	0.195	0.208	0.217	0.220	0.215	0.232	0.245	0.255	0.275	0.309	0.229
Shaanxi	0.191	0.185	0.190	0.200	0.203	0.207	0.218	0.229	0.244	0.256	0.262	0.276	0.222
Guizhou	0.141	0.148	0.160	0.173	0.178	0.186	0.192	0.212	0.219	0.225	0.244	0.247	0.194
Fujian	0.143	0.162	0.167	0.176	0.182	0.181	0.189	0.200	0.210	0.206	0.209	0.228	0.188
Gansu	0.147	0.149	0.153	0.164	0.160	0.166	0.178	0.192	0.201	0.219	0.226	0.241	0.183
Shanxi	0.149	0.157	0.16	0.165	0.157	0.159	0.168	0.178	0.192	0.198	0.203	0.222	0.176
Chongqing	0.109	0.113	0.116	0.122	0.128	0.131	0.138	0.150	0.157	0.169	0.176	0.187	0.141
Shanghai	0.070	0.121	0.127	0.136	0.144	0.154	0.162	0.176	0.173	0.094	0.094	0.104	0.130
Beijing	0.066	0.069	0.070	0.073	0.075	0.078	0.083	0.127	0.089	0.100	0.104	0.116	0.088
Ningxia	0.058	0.059	0.063	0.065	0.068	0.070	0.075	0.078	0.082	0.092	0.092	0.100	0.075
Tianjin	0.056	0.062	0.067	0.071	0.073	0.069	0.072	0.075	0.077	0.085	0.086	0.091	0.074
Hainan	0.046	0.048	0.056	0.054	0.060	0.061	0.070	0.075	0.081	0.094	0.104	0.113	0.072
Xizang	0.033	0.036	0.038	0.042	0.045	0.047	0.056	0.063	0.068	0.077	0.082	0.086	0.056
Qinghai	0.039	0.040	0.043	0.045	0.049	0.052	0.056	0.062	0.064	0.068	0.073	0.078	0.056

Notes: The data are calculated by the authors using the entropy method based on the AER evaluation indicators system.

Table A1 reveals obvious disparities in agricultural economic resilience across China's 31 provinces. Resilience values vary greatly among provinces and show a clear hierarchical distribution, with a notable gap between high-resilience and low-resilience provinces.

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