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Does Policy-Based Weather Index Insurance Enhance Agricultural Disaster Resilience? Empirical Evidence from 291 Prefecture-Level Cities in China

Lihao Tan[1,a], Qinglu Yuan[1,b,*]

[1]*School of Economics and Management, University of Emergency Management, Sanhe, China*
[a]*458765938@qq.com*, [b]*yuanqinglu@126.com*
**Corresponding author*

Abstract: *As a new type of agricultural risk management instrument, policy-based Weather index insurance is of great significance for enhancing agricultural disaster resilience across regions. This paper takes the data of 291 prefecture-level cities across the country from 2014 to 2023 as an example, and combines the TOPSIS-entropy method and the multi-period difference-in-differences model to deeply explore the impact and mechanism of policy-based Weather Index Insurance on agricultural disaster resilience. Research has found that the implementation of policy-based Weather Index Insurance has significantly enhanced agricultural disaster resilience, and this conclusion remains valid after multiple robustness tests. The results of the mechanism test show that the implementation of policy-based Weather Index Insurance significantly enhances the resilience of agricultural disasters by strengthening the level of agricultural insurance protection. The government's attention to climate risks and the level of agricultural socialized services can both have a positive moderating effect on the impact of policy-based Weather Index Insurance on agricultural disaster resilience. The impact of policy-based Weather Index Insurance on agricultural disaster resilience is more significant in grain-producing areas and low-altitude regions. This study provides data support and policy inspiration for further accelerating the promotion of policy-based Weather Index Insurance and enhancing the disaster resistance capacity of the national agricultural system.*

Keywords: *Policy-based Weather Index Insurance; Agricultural disaster resilience; DPSIR framework; Multi-period Difference-in-Differences Model; Agricultural insurance protection level*

1. Introduction

China is one of the countries most severely affected by natural disasters worldwide, with agriculture facing particularly severe disaster impacts. According to the 2025 National Basic Situation of Natural Disasters released by the Ministry of Emergency Management, direct economic losses caused by natural disasters reached 241.617 billion yuan in 2025, of which agriculture accounted for a large proportion, with a total affected crop area of 6.0694 million hectares [1]. The risks facing China's agricultural system are complex and diverse, fundamentally due to the weak foundation of agricultural and rural development, the ongoing exploration of modern agricultural systems, and the inherent vulnerability of agricultural production [2]. In addition, China's complex and variable geographical environment makes rural areas the primary bearers of natural disaster losses [3]. Existing studies have found that grain production resilience can be enhanced by developing new-quality productive forces (Liu Jing et al., 2025 [4]) and agricultural industrial resilience can be strengthened through promoting urban-rural integration (Li Hong et al., 2025 [5]), illustrating the capacity of agricultural systems to cope with certain crises. However, research on the inherent disaster resilience of agricultural systems remains insufficient.

To address such systemic risks, China is actively exploring risk management pathways centered on agricultural insurance. The 2024 Central Financial Work Conference emphasized leveraging the insurance industry's role as an economic shock absorber and social stabilizer, developing agricultural insurance, building a reinsurance market, and establishing a sound national catastrophe insurance system [6]. In 2025, China's agricultural insurance premium income reached 155.55 billion yuan, providing a cumulative risk protection of 5.3 trillion yuan [7]. Nevertheless, insurance coverage for high-value and regionally characteristic agricultural products remains relatively inadequate [8]. Furthermore, loss adjustment in traditional agricultural insurance is susceptible to subjective factors, frequently leading to claim disputes [9].

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In response to the dilemmas and deficiencies of traditional agricultural insurance, weather index insurance has emerged. Compared with traditional agricultural insurance, weather index insurance relies on publicly available data such as meteorological observations and regional yields, featuring high transparency and low verification thresholds, thereby mitigating information asymmetry and the associated moral hazard and adverse selection problems [10]. Weather index insurance can be categorized into policy-based and commercial types. Relative to commercial weather-index revenue insurance, policy-based weather-index revenue insurance serves as a more effective policy instrument for supporting agriculture [11]. However, the mechanism through which policy-based weather index insurance affects agricultural disaster resilience has not been systematically examined. Theoretically, by virtue of its index-triggered and automatic claim settlement mechanism, policy-based weather index insurance can shorten post-disaster compensation cycles and accelerate production recovery, thereby strengthening agricultural disaster resilience [12]. In practice, however, basis risk may undermine insurance effectiveness, reduce the perceived value of policy-based weather index insurance among farmers, lower voluntary demand, and result in suboptimal insurance uptake [13, 14].

Crucially, existing literature has not addressed a fundamental question: Does policy-based weather index insurance genuinely improve agricultural disaster resilience, and through what mechanisms does it exert such effects? Clarifying the impact mechanism of policy-based weather index insurance on agricultural disaster resilience is critical to the top-level design of the risk management system in China's agricultural modernization and carries profound policy implications.

This paper makes several potential marginal contributions. First, it enriches the theoretical connotation and measurement methods of agricultural disaster resilience. This study constructs a quantifiable comprehensive evaluation system for agricultural disaster resilience covering multiple dimensions including driving force, resistance, resilience, impact force, and transformation force, and analyzes the dynamic evolution of agricultural disaster resilience using kernel density estimation. Second, it employs a multi-period difference-in-differences(DID) model to reveal the impact mechanism of policy-based weather index insurance on agricultural disaster resilience, offering a new theoretical perspective for understanding the core role of innovative insurance instruments in agricultural risk management. Third, it expands the spatial-temporal scale of agricultural risk management research. Using a decade-long panel dataset covering 291 prefecture-level cities across China, this study substantially improves the reliability of empirical findings.

The remainder of this paper is structured as follows: Section 1 presents theoretical analysis and research hypotheses; Section 2 introduces the research design; Section 3 reports empirical results; and Section 4 concludes with policy recommendations.

2. Policy Background

Since 2014, Chinese government has encouraged the exploration of pilot projects for target price insurance of agricultural products such as grain and pigs . In 2016, the Central Committee of the Communist Party of China and The State Council issued the "Several Opinions on Implementing New Development Concepts, Accelerating Agricultural Modernization and Achieving the Goal of a Moderately Prosperous Society in All Respects", Weather Index Insurance was officially included in the Central Document No. 1 for the first time, marking its elevation from a local pilot program to a national level innovation direction in the agricultural insurance system. In June 2019, the Ministry of Finance issued the "Notice on Conducting Pilot Programs for Central Government's Financial Rewards and Subsidies for Local Advantageous and Characteristic Agricultural Products Insurance", including innovative insurance types such as Weather Index Insurance in the scope of central government's financial rewards and subsidies. The 2024 Central Financial Work Conference pointed out that the insurance industry should play the role of an economic shock absorber and social stabilizer, develop agricultural insurance, build a reinsurance market, and establish and improve the national catastrophe insurance security system . The No. 1 Central Document of 2025 points out that a multi-level agricultural insurance system should be improved, and support should be given to the development of insurance for characteristic agricultural products to address the problems of "high risks and weak protection" in characteristic industries .

Meanwhile, various regions in China are also actively responding to policies and implementing Weather Index Insurance led by prefectural-level units and supported by local finances. Among them, Zhejiang, Jiangsu and Guangdong in the east were the earliest regions in the country to implement Weather Index Insurance pilot programs. Zhejiang has the widest coverage, involving 12 types of

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

products such as tea, fruits and aquatic products, and is spread across more than 10 counties and cities including Hangzhou, Ningbo and Wenzhou. Guangdong has the most diverse range of insurance types, covering 8 categories including fruits, vegetables, aquatic products, flowers, etc., and covering 15 counties and cities in the Pearl River Delta and the eastern, western and northern parts of Guangdong. Jiangsu has performed outstandingly in facility agriculture, including facility greenhouses, open-field vegetables and aquatic product index insurance. Rice Weather Index Insurance is the most mature application target, widely distributed in North China and the Huang-Huai-Hai River Basin, including Beijing, Hebei, Shandong, Shanxi, Shaanxi, Jiangsu, Liaoning and other places, and is often linked to disaster factors such as drought and precipitation/drought. Fruit index insurance offers the most diverse range of products and the widest geographical coverage, including over 20 types such as apples (Luochuan, Shanxi), citrus fruits (Fujian, Jiangxi), lychees/mangoes (Hainan), winter jujubes (Hebei), grapes (Qinhuangdao, Hebei, Shanxi), durians (Sanya, Hainan), etc. In addition, Weather Index Insurance for characteristic agricultural products such as cash crops is being prioritized in core production areas, mainly responding to temperature, precipitation and comprehensive disaster factors.

3. Theoretical Analysis and Research Hypotheses

From the perspectives of loss compensation and claims settlement efficiency, policy-based weather index insurance determines losses based on objective meteorological data, avoiding the complex on-site loss-adjustment procedures of traditional agricultural insurance and greatly shortening the claim cycle. Meanwhile, the matching degree between indemnity amount and drought disaster losses reaches 65%–75%, significantly accelerating the pace of post-disaster production recovery for farmers [15]. In terms of risk prevention and incentive effects, farmers are still willing to adopt self-prevention measures to reduce actual losses while obtaining insurance coverage. The organic combination of ex ante prevention and ex post compensation strengthens the risk-resistance capacity of the agricultural system [16]. From an evolutionary perspective, a long-term and stable risk compensation mechanism can effectively mitigate the adverse impacts of disasters on the agricultural economic system, promote the transformation of agricultural production toward disaster-resistant and adaptive modes, and realize the shift of the agricultural system from passive disaster prevention to active disaster adaptation [17]. Accordingly, this paper proposes Hypothesis H1:

Hypothesis H1: Policy-based weather index insurance in China exerts a positive impact on agricultural disaster resilience.

Policy-based weather index insurance overcomes moral hazard, adverse selection, and high transaction costs inherent in traditional agricultural insurance, thereby addressing problems including low farmers' willingness to participate, low insurance penetration, and insufficient insurance depth. From the perspective of prospect theory, smallholder farmers' demand for policy-based weather index insurance is negatively correlated with their degree of loss aversion. If insurance contract design explicitly covers meteorological disasters, it can enhance smallholders' trust in and demand for insurance. Through fiscal leverage and subsidies, farmers' willingness to insure is stimulated, further improving the penetration and coverage depth of agricultural insurance [18,19]. Benefiting from the central government's reward-for-subsidy policy for specialty agricultural product insurance, the coverage level of specialty agricultural product insurance represented by policy-based weather index insurance has grown rapidly, further elevating the overall protection level of agricultural insurance [20]. Improved protection reduces risks in agricultural production, incentivizes farmers to optimize planting structures, expand production scales, and increase long-term investment in disaster-resistant agricultural technologies [21]. Such a buffer provided by agricultural insurance protection can significantly strengthen the agricultural system's ability to absorb shocks and recover autonomously. Accordingly, this paper proposes Hypothesis H2:

Hypothesis H2: Policy-based weather index insurance can improve agricultural disaster resilience by enhancing the protection level of agricultural insurance.

According to risk aversion theory, intensifying climate risk increases uncertainty in agricultural production and raises farmers' demand for risk hedging, prompting them to participate in policy-based agricultural insurance such as policy-based weather index insurance for risk transfer [22]. In addition, the government's popularization of meteorological knowledge and publicity guidance through multiple channels reduces information asymmetry between farmers and insurance companies and improves public responsiveness to climate risks [23]. When the government attaches high attention to climate risks, policy-based weather index insurance can form institutional synergy with the government's ex ante disaster prevention and mitigation system, thereby significantly enhancing agricultural disaster resilience.

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

Accordingly, this paper proposes Hypothesis H3a:

Hypothesis H3a: Government attention to climate risk plays a positive moderating role in the impact of policy-based weather index insurance on agricultural disaster resilience.

Agricultural socialized service entities usually share agricultural production income with farmers in the form of fixed output or fixed income payments. Therefore, insurance companies can provide policy-based or commercial agricultural insurance products to such service entities to diversify their risks and stabilize their returns. Agricultural socialized services can expand the radiation and driving effects of fiscal support policies and implement support policies for innovative agricultural insurance instruments such as policy-based weather index insurance [24]. Supply and marketing cooperatives cooperate with insurance companies to develop differentiated insurance products, achieving full coverage of disaster types and protection levels. By piloting policy-based weather index insurance for agricultural products and hedging price risks through futures markets, the claim settlement cycle for farmers is shortened, risk response efficiency is improved, and farmers' willingness to purchase policy-based weather index insurance is enhanced. Therefore, this paper proposes Hypothesis H3b:

Hypothesis H3b: Agricultural socialized services play a positive moderating role in the impact of policy-based weather index insurance on agricultural disaster resilience.

The theoretical transmission mechanism of this article is as follows in Figure 1:

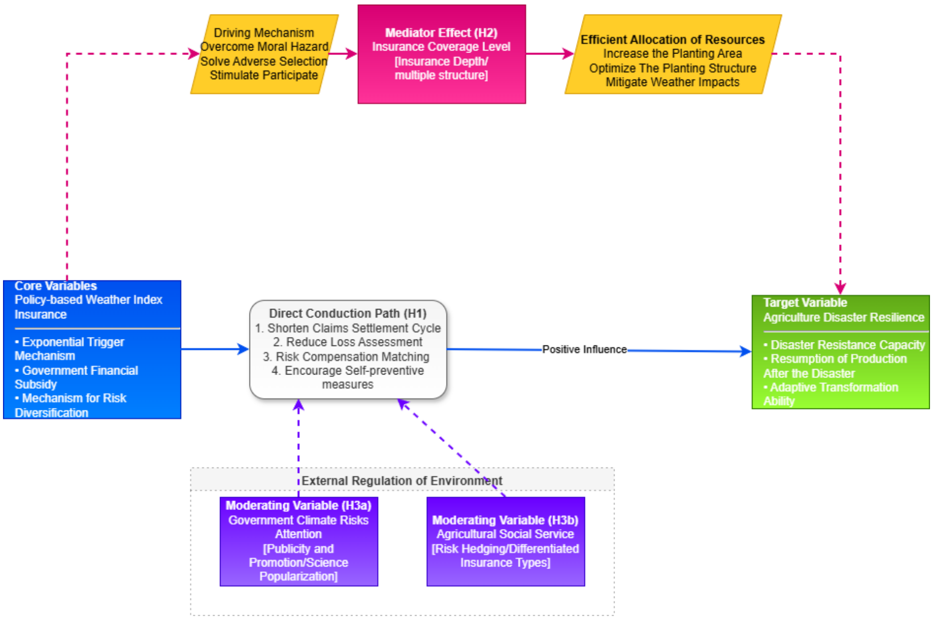


Figure 1: Theoretical transmission mechanism.

4. Research Design

4.1. Establishment of Index System

In Figure 2, Compared with the traditional Pressure-State-Response (PSR) framework, the Driving Force-Pressure-State-Impact-Response (DPSIR) framework extends the causal chain and incorporates external driving factors, enabling a better analysis of positive and negative feedback effects for risk assessment and management [25]. At present, this framework has been adopted by agricultural researchers to analyze prominent agricultural environmental problems and the ability of agricultural systems to maintain core functions and recover from external shocks [26,27]. Accordingly, this framework can also be applied to analyze the capacity of agricultural systems to cope with severe disasters. Based on the above analysis and in accordance with principles of scientific rigor and data availability, this paper constructs an indicator system for agricultural disaster resilience under the DPSIR framework, as detailed in Table 1.

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

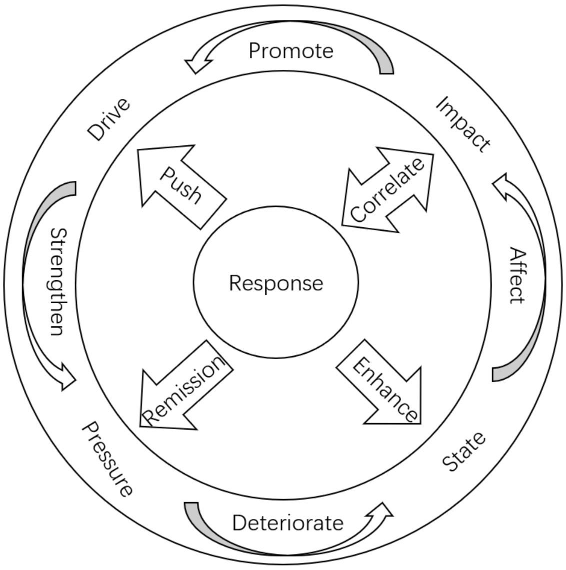


Figure 2: DPSIR Frame.

Table 1: Indicator System for Agricultural Disaster Resilience.

Target Layer	Criterion Layer	Indicator Layer	Indicator Direction	Weight
Agricultural Disaster Resilience	D (Driving Force)	Per capita disposable income of rural residents	+	0.043
		Growth rate of the rural primary industry	+	0.031
		Digital inclusive finance index	+	0.039
		Human capital level	+	0.067
		Education expenditure level	+	0.033
	P (Pressure)	Proportion of annual extreme weather days	-	0.109
		Climate policy uncertainty index	-	0.042
		Agricultural mechanization level	+	0.050
	S (State)	Effective sown area of crops	+	0.058
		Forest coverage rate	+	0.031
		Per capita road area	+	0.043
		Number of health technicians per 1,000 rural residents	+	0.040
	I (Impact)	Rural poverty incidence	-	0.031
		Average indemnity per crop	+	0.112
		Contribution rate of compensation for affected farmers	+	0.078
	R (Response)	Scale of agricultural disaster risk reserve fund	+	0.071
		Number of farmers' cooperatives	+	0.056
		Green technology innovation level	+	0.035
		Survival rate of green agricultural enterprises	+	0.031

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

As a multi-objective decision-making method, the TOPSIS technique calculates the distances between each evaluation object and the positive/negative ideal solutions, derives the relative closeness of each sample to the ideal solution, and ranks all samples. A higher relative closeness value indicates a higher level of agricultural disaster resilience, and vice versa. Combined with the entropy weight method for objective weight assignment, this paper adopts the TOPSIS-entropy weight integrated model to measure agricultural disaster resilience, systematically quantifies the agricultural disaster resilience of prefecture-level cities nationwide, and conducts kernel density estimation. The specific procedures are as follows:

The standardization formula for positive indicators is:

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

The standardization formula for negative indicators is:

$$y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{2}$$

Where: y_{ij} denotes the standardized value of the j-th agricultural disaster resilience indicator for the i-th evaluation unit; $\max(x_j)$ and $\min(x_j)$ represent the maximum and minimum raw values of the j-th agricultural disaster resilience indicator across all evaluation units, respectively.

Based on the standardized matrix of agricultural disaster resilience indicators, we calculate the proportion p_{ij} of the j-th resilience indicator for the i-th evaluation unit. This proportion reflects the relative performance of the evaluation unit under the corresponding indicator and characterizes the differentiation degree among all units on this indicator. The formula is specified as follows:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}} \tag{3}$$

Where $k = \frac{1}{\ln n}$ is the correction coefficient.

Based on the coefficient of difference, we calculate the entropy weight w_j of each agricultural disaster resilience indicator. The sum of all entropy weights satisfies $\sum_{j=1}^{m} w_j = 1$, which can objectively reflect the importance of each indicator in the comprehensive evaluation of disaster resilience. The formula is specified as follows:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} 1 - e_j} \tag{4}$$

Combining the objective weights of agricultural disaster resilience indicators derived from the entropy weight method with the TOPSIS method, we compute the comprehensive agricultural disaster resilience score for each evaluation unit and rank the units to distinguish their resilience levels. Multiply the standardized value y_{ij} of each agricultural disaster resilience indicator by its entropy weight w_j to construct a weighted standardized matrix. This eliminates the impact of weight disparities across different resilience indicators and highlights the contribution of high-weight indicators to agricultural disaster resilience. The formula is as follows:

$$z_{ij} = w_j \cdot y_{ij} \tag{5}$$

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

In the comprehensive evaluation of agricultural disaster resilience, the positive ideal solution Z^{+} refers to the set of optimal values of weighted standardized resilience indicators, corresponding to the ideal state with the strongest agricultural disaster resilience; the negative ideal solution Z^{-} refers to the set of worst values of weighted standardized resilience indicators, corresponding to the state with the weakest agricultural disaster resilience. The specific formulas are shown below:

$$Z^{+}=(z_1^{+},z_2^{+},\ldots,z_m^{+}) \tag{6}$$

$$Z^{-}=(z_1^{-},z_2^{-},\ldots,z_m^{-}) \tag{7}$$

The comprehensive score S_i measures the proximity between the agricultural disaster resilience level of the i-th evaluation unit and the optimal resilience state. A higher score indicates stronger agricultural disaster resilience for the unit. The formula is presented as:

$$S_i=\frac{\sqrt{\sum_{j=1}^{m}(z_{ij}-z_j^{-})^2}}{\sqrt{\sum_{j=1}^{m}(z_{ij}-z_j^{+})^2}+\sqrt{\sum_{j=1}^{m}(z_{ij}-z_j^{-})^2}} \tag{8}$$

Let $R=\{r_1,r_2,\ldots,r_m\}$ denote the sample dataset of agricultural disaster resilience for a given research year, where r_i represents the agricultural disaster resilience value of the i-th sample and m is the total sample size. The kernel density estimator at an arbitrary value r is defined as:

$$\hat{f}(r)=\frac{1}{mh}\sum_{i=1}^{m}K\left(\frac{r-r_i}{h}\right) \tag{9}$$

Where r denotes the agricultural disaster resilience value to be estimated for density; r_i is the observed agricultural disaster resilience value of the i-th sample; m stands for the number of agricultural disaster resilience samples; h is the bandwidth, and K is the kernel function. This paper adopts the Gaussian kernel for kernel density estimation of agricultural disaster resilience, and the explicit form of the kernel function is:

$$K(u)=\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{u^2}{2}\right) \tag{10}$$

where $u=\frac{r-r_i}{h}$. Substitute u into the core formula to obtain the complete expression for kernel density estimation of agricultural disaster resilience:

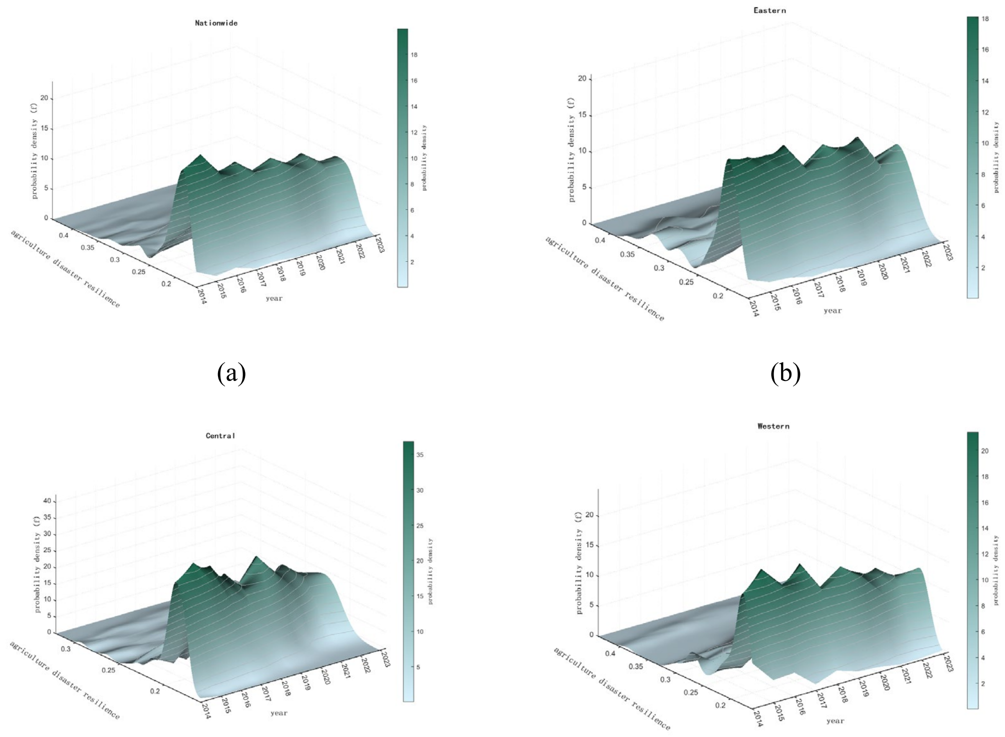
$$\hat{f}(r)=\frac{1}{mh\sqrt{2\pi}}\sum_{i=1}^{m}\exp\left(-\frac{(r-r_i)^2}{2h^2}\right) \tag{11}$$

4.2. Result Analysis

In line with economic attributes and geographical features, China is categorized into Eastern, Central and Western regions in this study. Matlab is adopted to plot the kernel density curves of agricultural disaster resilience, with the visualized results presented in Figure 3. From the dynamic evolution of kernel density for nationwide as well as three regional resilience levels over 2014–2023, all distribution curves shift rightward year by year, demonstrating a steady improvement in agricultural disaster resilience across all regions of China. From the distribution perspective, the peak heights of nationwide, Eastern and Western curves decline amid fluctuations alongside a broadening distribution range, which reflects uneven growth rates of resilience among different regions. By contrast, the Central region shows prominent concentration characterized by relatively high peaks, implying highly similar agricultural disaster resilience across prefecture-level cities within this area. In terms of distribution ex-tension, all

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

curves feature obvious right-skewed tails during evolution, and the Eastern region has a longer right tail. This indicates that several prefecture-level cities in Eastern China take a leading position in resilience development, whereas the striking regional disparity persists between high-resilience pioneer areas and underdeveloped catching-up regions.



(a) (b)

(c) (d)

Figure 3: Kernel Density Estimation of Agricultural Disaster Resilience.

4.3. Variable Definitions

Dependent Variable: Consistent with the foregoing analysis, this paper adopts agricultural disaster resilience (adr) as the dependent variable.

Independent Variable: Following the prior discussion, regions that implement policy-based weather index insurance are assigned $treat=1$ to form the treatment group, while regions without such policies are assigned $treat=0$ to form the control group. Considering the staggered policy rollout across prefecture-level cities, we set $time=0$ for years before policy implementation and $time=1$ for post-implementation years. The interaction term $did = treat*time$ is then constructed.

Mechanism Variables: Drawing on the previous analysis, agricultural insurance coverage level (aid) is selected as the mediating variable for the impact of policy-based weather index insurance on agricultural disaster resilience; government attention to climate risk (cra) and agricultural socialized service level (ssl) are chosen as moderating variables.

Control Variables: Referring to existing studies on agricultural anti-disaster capacity [28,29], this paper selects urbanization rate (ur), fixed asset investment (fai), fiscal expenditure for agriculture (fsa), and agricultural technological innovation level (fsa) as control variables.

4.4. Model Specification

This paper regards the initial launch of policy-based weather index insurance in each prefecture-level city as a quasi-natural experiment. The DID model effectively eliminates the bias of time heterogeneity on policy effects. After incorporating city fixed effects, the estimation results capture the policy-induced changes in agricultural disaster resilience. Conventional DID models fail to address staggered policy

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

implementation across different batches, so this paper constructs a multi-period DID Model as follows:

$$adr_{it} = \alpha_0 + \alpha_1 did_{it} + \alpha_2 control_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{12}$$

Where adr_{it} denotes the agricultural disaster resilience of prefecture-level city i in year t; α_0 is the intercept term; the coefficient α_1 reflects the policy effect of policy-based weather index insurance for city i in year t; did_{it} indicates whether city i implemented the policy in year t; $control_{it}$ represents the set of control variables; μ_i stands for city fixed effects; θ_t denotes year fixed effects; and ε_{it} is the random disturbance term.

The traditional three-step mediation approach suffers from endogeneity issues. Following Jiang Ting (2022) [30], this paper establishes a mediation effect model to identify the influencing mechanism of policy-based weather index insurance on agricultural disaster resilience, specified as:

$$aid_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 control_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{13}$$

Where aid_{it} refers to the agricultural insurance coverage level of prefecture-level city i in year t.

To further explore how other factors moderate the impact of policy-based weather index insurance on agricultural disaster resilience, we construct the following moderation effect model:

$$adr_{it} = \gamma_0 + \gamma_1 did_{it} + \gamma_2 M_{it} + \gamma_3 did_{it} \times M_{it} + \gamma_4 control_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{14}$$

Where M represents the moderating variables, i.e., government attention to climate risk (cra) and agricultural socialized service level (ssl). γ_3 captures the magnitude of the moderating effect exerted by cra and ssl.

5. Research Design

5.1. Baseline Regression

Consistent with the foregoing theoretical framework, this paper adopts the multi-period DID model to regress the impact of policy-based weather index insurance on agricultural disaster resilience, and the estimation results are reported in Table 2. As shown in Model 1, after controlling for city and year fixed effects, the coefficient of policy-based weather index insurance on agricultural disaster resilience is 0.0876 and statistically significant at the 5% level. After adding control variables in Model 2, the significance level and sign of the core coefficient remain unchanged. This verifies that policy-based weather index insurance exerts a prominent positive driving effect on agricultural disaster resilience, which supports Hypothesis H1.

Table 2: Baseline Regression Results.

Variable	Model 1
did	0.0876** (0.0362)
Control Variables	No
City Fixed Effects	Yes
Year Fixed Effects	Yes
Constant	-14.8299*** (0.0104)
Observations	2910
R^2	0.938

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively; standard errors are reported in parentheses, the same below.

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

5.2. Robustness Tests

To further enhance the reliability and stability of the baseline regression results, three approaches are adopted to conduct robustness checks:

5.2.1. Parallel Trend Test

This paper incorporates dummy variables for years before and after the implementation of policy-based weather index insurance to clearly observe the dynamic changes of estimation coefficients. To avoid collinearity bias, the year prior to policy implementation (j=-1) is set as the reference group. As illustrated in Figure 4, the regression coefficients are not statistically significant and fluctuate around 0 before the launch of policy-based weather index insurance, which indicates no significant difference between the treatment group and control group prior to policy rollout and satisfies the parallel trend assumption. In the policy implementation year and all subsequent years, the estimated coefficients are significantly positive at the 10% significance level and show an upward trend. This demonstrates that agricultural disaster resilience continuously improves after the policy launch, and the policy effect is pronounced.

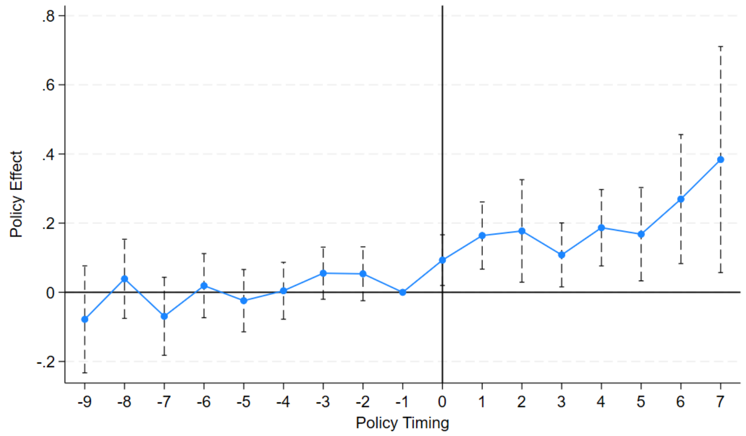


Figure 4: Parallel Trend Test.

5.2.2. Placebo Test

We randomly select 127 prefecture-level cities as the treatment group from the full sample, with the rest serving as the control group. The placebo test is conducted by randomly assigning policy implementation cities and time points, and the procedure is repeated 500 times to obtain Figure 5. The results show that the estimated coefficients of the placebo regression roughly follow a normal distribution, with only a tiny fraction of coefficients falling to the right of the baseline regression coefficient. This indicates that the baseline regression results are barely affected by unobservable city-year confounding factors, and the placebo test is passed, which further verifies the robustness of the baseline findings.

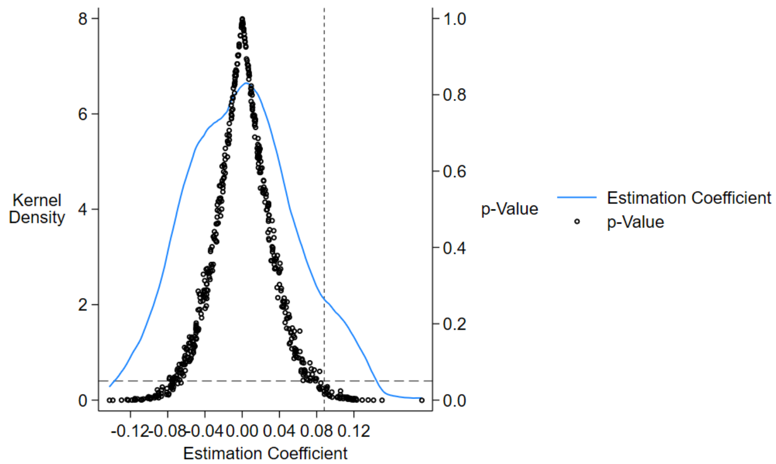


Figure 5: Placebo Test.

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

5.2.3. Double Machine Learning

Traditional econometric models are limited in capturing complex nonlinear relationships, while machine learning models can better capture nonlinear effects and interaction terms in the dataset, effectively mitigating omitted variable bias in standard DID models and more accurately identifying the net policy effect. This paper adopts sample split ratios of 1:2 and 1:4, and applies quantile regression, elastic net, neural network and other algorithms for regression. The results are reported in Table 3. Regardless of the machine learning algorithm or sample split ratio adopted, the regression coefficients of policy-based weather index insurance on agricultural disaster resilience are significantly positive at the 5% level and consistent with the baseline regression outcomes. This proves that the core findings of this paper are not biased due to omitted variables and confirms the robustness of our results.

Table 3: Regression Results of Double Machine Learning.

Variable	Quantile Regression	Elastic Net	Neural Network	Quantile Regression	Elastic Net	Neural Network
	0.1343*** (0.0391)	0.1139*** (0.0374)	0.1268*** (0.0429)	0.1279*** (0.0374)	0.1279*** (0.0374)	0.0988*** (0.0432)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample Split Ratio	1:2	1:2	1:2	1:4	1:4	1:4
Observations	2910	2910	2910	2910	2910	2910

5.3. Endogeneity Analysis

This paper adopts the density of rural financial institution branches as the instrumental variable and employs two-stage least squares (2SLS) to alleviate endogeneity bias in the benchmark model. Dense rural financial outlets facilitate offline insurance service handling. The policy-based weather index insurance products lower farmers' insurance participation costs, raise farmers' willingness to enroll, and promote the popularization of such insurance, satisfying the relevance requirement for instrumental variables. Meanwhile, the distribution of rural financial branches is determined by the industrial layout of local financial sectors, and changes in agricultural disaster resilience are unrelated to branch distribution, satisfying the exogeneity requirement for instrumental variables. As shown in Table 4, the Kleibergen-Paap rk LM statistic equals 33.25, significant at the 1% level, which rejects the null hypothesis of "under identification". The Cragg-Donald Wald F statistic is 30.34, far exceeding the 10% critical value of 16.38, eliminating the weak instrumental variable concern. The first-stage estimation shows the instrumental variable exerts a significantly positive impact on the core explanatory variable did. The second-stage results reveal that the did coefficient remains significantly positive at the 5% level and consistent with the baseline regression results. This means that after addressing endogeneity, policy-based weather index insurance still significantly improves agricultural disaster resilience, further validating the robustness of our conclusions.

Table 4: Instrumental Variable Estimation Results

Variable	First Stage	Second Stage
did		0.7957** (0.3982)
IV	0.5079*** (0.0922)	
Control Variables	Yes	Yes
City Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Cragg-Donald Wald F statistic	30.34(16.38)	
Kleibergen-Paap rk LM statistic	33.25***	
Endogeneity test	4.208**	
Observations	2910	2910

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

5.4. Mechanism Tests

The foregoing theoretical analysis indicates that policy-based weather index insurance can stabilize the revenue of new agricultural business entities by raising agricultural insurance coverage levels, thereby enhancing agricultural disaster resilience. Accordingly, this paper selects agricultural insurance coverage level as the mediating variable to further explore the transmission mechanism through which policy-based weather index insurance affects agricultural disaster resilience. The estimation results in Table 5 (Model 2) show that the regression coefficient of agricultural insurance coverage level is 0.1705 and significantly positive at the 1% level, which confirms that agricultural insurance coverage exerts a prominent boosting effect. Diversified agricultural insurance models improve the scientificity of agricultural insurance underwriting and claim settlement. When farmers suffer losses from natural disaster shocks, agricultural insurance coverage can effectively compensate agricultural operating losses and strengthen regional disaster resistance [31,32]. To verify the stability of this mediating effect, we re-run regressions for the full sample and conduct bootstrap tests, as displayed in Table 5 (Bootstrap b1 column). After simultaneously controlling for policy pilot cities, agricultural insurance coverage and agricultural disaster resilience, the coefficients of policy-based weather index insurance and agricultural insurance coverage remain significant at the 5% level or above, proving that higher agricultural insurance coverage induced by policy-based weather index insurance effectively lifts agricultural disaster resilience and verifying the validity of this transmission channel, which supports Hypothesis H2.As implied by the previous theoretical hypotheses, government attention to climate risk and agricultural socialized services may moderate the relationship between policy-based weather index insurance and agricultural disaster resilience. Therefore, this paper introduces government climate risk attention and agricultural socialized service level as moderating variables, adds their interaction terms with did into the regression, and presents the results in Table 5 (Model 3 & Model 4). The interaction coefficients are significantly positive at the 10% level, which demonstrates that government attention to climate risk and agricultural socialized services can positively reinforce the boosting effect of policy-based weather index insurance on agricultural disaster resilience, verifying Hypotheses H3a and H3b.

Table 5: Mechanism Regression Results

Variable	Model 1	Model 2	Model 3	Model 4
did	0.1176** (0.0351)	0.0681** (0.0349)	0.0758** (0.0356)	0.0318 (0.0879)
aid		0.1705*** (0.3471)		
cra			-0.3877*** (0.1698)	
ssl				0.05359 (0.0879)
cra×did			0.5433** (0.3165)	
ssl×did				0.1793** (0.0856)
Control Variables	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bootstrap b1 Test		[0.0322,0.0694]		
Observations	2910	2910	2910	2910
	0.7819	0.9392	0.9378	0.9380

5.5. Heterogeneity Analysis

The above discussion explores the overall impact and transmission channels of policy-based weather index insurance on agricultural disaster resilience, yet it fails to address whether regional differences alter such effects. To fill this gap, this paper conducts heterogeneity analysis from three dimensions: agricultural industrial agglomeration, grain-producing regions, and altitude zones, with results summarized in Table 6.

As shown in the table, policy-based weather index insurance exerts a significant positive impact on agricultural disaster resilience in regions with low agricultural industry share, major grain-producing areas, and low-altitude zones. In regions with a small proportion of agricultural industries, traditional

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

disaster prevention resources are relatively scarce, and farmers have weak capacity to bear climate risks; policy-based weather index insurance can resolve problems of difficult loss assessment, high moral hazard and adverse selection, stabilize agricultural production and farmers' income, and generate a more pronounced marginal improvement in agricultural disaster resilience. As the core food security base of the country, major grain-producing areas feature large-scale and intensive agricultural operations. Policy-based weather index insurance mitigates production losses caused by meteorological disasters, stabilizes the production cycle of business entities, and thus elevates the capacity and efficiency of the agricultural system to withstand disasters. Low-altitude areas are primary agricultural production zones with concentrated farmland and dense crop cultivation, and are frequently exposed to extreme meteorological disasters including heavy rain, floods and heatwaves. Policy-based weather index insurance adopts objective meteorological data as the trigger standard to realize rapid claim settlement. Therefore, introducing such insurance in these regions delivers a more prominent boost to local agricultural disaster resilience.

Table 6: Heterogeneity Analysis Results

Variable	Low Agricultural Industry Share	High Agricultural Industry Share	Grain-Producing Areas	Non-Grain-Producing Areas	Low-Altitude Zones	High-Altitude Zones
did	0.0977*** (0.0534)	0.0411 (0.0460)	0.0791*** (0.0385)	0.0821** (0.0621)	0.0927*** (0.0375)	-0.0585 (0.1085)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-15.6198***	-13.0759***	-13.9832***	-14.2533***	-13.5143***	-17.4137***
Observations	1450	1460	1680	1230	2380	530

6. Conclusions and Policy Implications

Based on panel data covering 291 prefecture-level cities in China, this paper calculates agricultural disaster resilience scores from 2014 to 2023 under the DPSIR framework, empirically examines the impact of policy-based weather index insurance on agricultural disaster resilience, and tests the mediating role of agricultural insurance coverage as well as the moderating roles of government climate risk attention and agricultural socialized service level. A series of robustness tests and heterogeneity analyses are further implemented. The core findings are as follows:

First, the implementation of policy-based weather index insurance generates a significant positive effect on agricultural disaster resilience, and it can strengthen resilience by lifting agricultural insurance coverage levels.

Second, both government attention to climate risk and agricultural socialized services positively moderate the impact of policy-based weather index insurance on agricultural disaster resilience.

Third, the impact of policy-based weather index insurance on agricultural disaster resilience presents evident regional heterogeneity, with more pronounced effects in major grain-producing areas and low-altitude regions.

Combined with the above conclusions, this paper puts forward the following policy recommendations:

Expand the coverage of policy-based weather index insurance. Prefecture-level governments should precisely allocate policy dividends to policy-based weather index insurance and continuously expand insurance coverage. The 2026 Central Government No.1 Document explicitly calls for "supporting the development of insurance for local characteristic agricultural products and improving the efficiency of claim settlement" [33]. Prefecture-level governments should develop tailored policy-based weather index insurance products targeting dominant local crops and frequent meteorological disasters, reduce farmers' insurance participation costs, and ensure full implementation of the insurance system.

Strengthen the cultivation of climate risk awareness and the development of agricultural socialized services. Prefecture-level governments should popularize basic knowledge of policy-based weather index insurance through rural radio, agricultural technical training, and online lectures. On this basis, they

ISSN 2616-5910 Vol. 7, Issue 1: 48-62, DOI: 10.25236/AJALS.2026.070108

should integrate socialized service resources such as agricultural technology extension, disaster prevention and mitigation, and claims assistance to accelerate the promotion of policy-based weather index insurance.

Implement differentiated strategies for policy-based weather index insurance. For major grain-producing regions, policy priorities should focus on core staple crops including rice, wheat, and corn. Special subsidies can reduce risk costs for large-scale agricultural operators and achieve full-cycle crop protection. For low-altitude areas prone to high temperatures and floods, insurance clauses and trigger thresholds should be optimized to improve the sensitivity of policy-based weather index insurance products, thereby further enhancing the role of such insurance in boosting agricultural disaster resilience.

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