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How Agricultural Insurance and Farmland Infrastructure Affect Grain Production Resilience Under Climate Shocks in China

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Abstract

This study defines grain production resilience as the stability of grain output under climate-related disturbances, measured by the negative value of the three-year rolling coefficient of variation of grain output. It incorporates agricultural insurance and farmland infrastructure into a unified analytical framework and treats climate shocks as state variables to examine their effects on grain production resilience and their interaction. Using panel data for 31 provinces in China from 2008 to 2024, this study constructs temperature and precipitation shock indices based on ERA5 data and estimates a panel smooth transition regression model. The results show that climate shocks significantly weaken grain production resilience, and their effects are nonlinear and state dependent. Farmland infrastructure has a relatively stable positive effect, whereas agricultural insurance plays a weaker role. Under temperature shocks, the two policy tools tend to exhibit a substitutive relationship. Under precipitation shocks, however, their relationship varies across shock regimes and becomes more complementary only under higher-shock conditions. These findings suggest that grain production support policies should be adjusted according to the type and intensity of climate shocks.

Keywords: agricultural insurance; farmland infrastructure; climate shocks; grain production resilience; panel smooth transition regression

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1. Introduction

Climate change and extreme weather events are continuously increasing pressure on global food security. A report released by the World Meteorological Organization (WMO) shows that 2024 will be the warmest year on record, with drought and other climate shocks exacerbating food crises in many countries and further increasing the risk of acute food insecurity globally [1]. Many studies also indicate that rising temperatures, abnormal precipitation, and frequent extreme weather events have already had a systemic negative impact on grain production. This has not only weakened agricultural output levels but also exacerbated the volatility and vulnerability of agricultural production [2–5]. At the same time, climate change will further weaken the long-term stability and growth potential of agricultural production systems by disrupting crop growth cycles, affecting resource allocation efficiency, and altering agricultural input decisions [6,7]. Against this backdrop, enhancing the ability of agricultural systems to maintain production, absorb risks, and recover function under climate shocks has become a core issue in food security research.

This issue is particularly prominent in China. As one of the world's largest grain producers, China has consistently maintained a high level of total grain output in recent years. Data from the National Bureau of Statistics shows that the country's total grain output reached 706.5 million tons in 2024 and further increased to 714.88 million tons in 2025 [8,9]. Meanwhile, the Food Security Law of the People's Republic of China, which officially came into effect on June 1, 2024, further highlights the important position of food security in the national strategy [10]. However, the continued growth in total grain output does not mean that the grain production system has escaped the constraints of climate risks. On the contrary, against the backdrop of widening regional climate differences and increasingly frequent extreme weather events, the systemic vulnerability of grain production is still rising. Existing research also shows that Chinese agriculture is highly sensitive to climate change; rising temperatures and abnormal precipitation can significantly affect grain yields and their volatility [5]. Therefore, focusing solely on grain output levels or fluctuations is insufficient to fully characterize the stability of grain supply. In contrast, grain production resilience better reflects the agricultural system's ability to maintain function, adapt to change, and gradually recover under climate disturbances. In recent years, related research has gradually shifted its focus from simply output to emphasizing resilience—the agricultural system's ability to maintain operation and dynamically adjust under external shocks [11–13].

At the policy response level, agricultural insurance and farmland infrastructure are generally considered two important climate adaptation tools, but their mechanisms of action differ. Agricultural insurance primarily reduces uncertainty faced by farmers through risk transfer and income smoothing mechanisms, thereby influencing their production decisions and factor input behavior. Theoretical research shows that risk reduction can increase farmers' optimal input levels [14]; empirical studies have also found that insurance incentivizes farmers to increase high-yield but high-risk productive inputs [15,16]. In contrast, farmland infrastructure plays a more significant role in improving production conditions. It directly strengthens the material basis for agricultural systems to cope with climate shocks by improving irrigation, alleviating water constraints, and enhancing resource allocation efficiency [17,18]. Although existing literature discusses the roles of these two policy tools separately, our understanding of their relationship remains limited. On the one hand, risk mitigation mechanisms may increase agricultural operators' willingness to invest in production, thus complementing infrastructure [19]. On the other hand, under conditions of limited fiscal resources or distorted policy incentives, insurance subsidies may crowd out long-term infrastructure investment, thus exhibiting a certain degree of substitutability [20,21]. Therefore, there is no naturally stable complementary or substitutive relationship between agricultural insurance and farmland infrastructure; their interaction is more likely to dynamically adjust with changes in the risk environment and institutional conditions.

Furthermore, both climate shocks themselves and the effects of policy tools can exhibit significant nonlinear characteristics, a point that has not been adequately addressed in existing policy evaluation research. Previous studies have shown that the relationship between temperature and agricultural output is often not linear but rather exhibits a clear threshold effect; once temperatures exceed a certain critical level, yield losses rapidly amplify [22,23]. The impacts of extreme climate events on agricultural and economic systems also often exhibit asymmetric and nonlinear characteristics [24]. Simultaneously, the adaptability of agricultural systems is not constant. Under mild climate fluctuations, farmers can buffer some of the shock by adjusting planting structures, input combinations, or adopting new technologies; however, as the intensity of climate shocks continues to rise, this adaptation space may shrink significantly, and losses will intensify [6,25]. Ignoring the nonlinear characteristics of climate shocks, analyses based on linear models may not only underestimate the extent of losses under extreme scenarios but may also obscure the differentiated effects of different policy tools under different climate conditions. In other words, the effectiveness of agricultural policy tools is likely to be significantly state-dependent and needs to be identified within a nonlinear analysis framework.

Based on this, this paper incorporates agricultural insurance and farmland infrastructure into a unified analytical framework and introduces climate shock as a state variable to examine the effects of these two types of policy tools on the resilience of grain production and their interrelationships under different climate scenarios. Compared with existing research, this paper makes three main contributions. First, this paper examines climate shock and policy response from the perspective of

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grain production resilience, moving beyond the traditional approach of measuring agricultural performance solely by yield or yield fluctuations, thus more closely reflecting the stability and adaptability characteristics of agricultural systems under climate pressure. Second, this paper no longer separates agricultural insurance and farmland infrastructure, but examines their roles simultaneously within a unified framework, further identifying whether they are complementary or substitutive under different climate shock intensities, thereby providing new empirical evidence for understanding the interaction mechanisms between policy tools. Third, this paper uses climate shock as a transformation variable and employs a panel smoothed transformation regression model to identify the nonlinearity and state-dependent characteristics of policy effects, thereby revealing the changing process of the marginal effects of policy tools under different climate states. Empirical analysis based on provincial panel data from China also provides more targeted evidence for optimizing the policy mix for supporting grain production in the context of climate change.

The remaining parts of this paper are arranged as follows: Section 2 reviews the relevant literature and develops the research hypothesis. Section 3 introduces the data, variables, and empirical model. Section 4 presents the empirical results. Section 5 reports further analysis and robustness checks. Section 6 concludes with policy implications.

2. Literature Review

2.1. Climate Shocks and Grain Production Resilience

Numerous studies have shown that climate shocks have significant and multidimensional impacts on agricultural production, manifesting not only as decreased output levels but also as increased output volatility and reduced production stability [2–5,7]. Lobell et al. [2], based on cross-national data, were among the first to point out that the climate change trends observed since 1980 have negatively impacted global maize and wheat yields, indicating that climate change is not merely a long-term background condition but has become a real constraint on staple grain production. Ray et al. [3] further found that climate variability can explain a significant portion of the fluctuations in global major crop yields, and that climate factors have a significant impact on interannual fluctuations in many important grain-producing regions. Regarding extreme events, Lesk et al. [4] pointed out that droughts and extreme heat significantly reduce a country’s grain output, indicating that climate shocks not only affect agricultural production through gradual changes in average climate conditions but also directly impact grain supply through sudden and intense disturbances. Zhao et al. [5] further confirmed on a global scale that global warming has a systemic negative impact on the yields of major grain crops. Furthermore, Ortiz-Bobea et al. [7] pointed out that anthropogenic climate change has slowed global agricultural productivity growth, meaning that climate stress not only causes current output losses but also weakens the dynamic potential for sustained growth in agricultural systems.

Overall, existing research has sufficiently demonstrated the significant impact of climate shocks on agricultural performance, but most literature still focuses primarily on yield levels or interannual fluctuations. In contrast, recent research has begun to emphasize a resilience perspective, providing a different understanding path for agricultural systems analysis than the traditional output framework [11–13]. Darnhofer [11] points out that resilience not only means buffering capacity but also the ability of agricultural operators to adapt and adjust to changing environments. Tendall et al. [12] extends this concept to a broader level of grain systems, arguing that resilience emphasizes the system’s ability to continuously provide grain under various, even unforeseen, shocks. Similarly, Urruty et al. [13] distinguishes resilience from related concepts such as stability and robustness, emphasizing that the performance of agricultural systems should be examined in extreme and uncertain environments. Therefore, measuring agricultural performance solely by output or yield per unit area is insufficient, as these indicators primarily reflect predetermined outcomes and cannot fully characterize the production system’s ability to maintain, recover from, and adjust under shocks. Based on this, analyzing climate shocks from the perspective of grain production resilience is more helpful in understanding the ability of agricultural systems to maintain function and sustainable supply under climate disturbances. However, compared with the large amount of research on output loss and fluctuation, the literature directly discussing grain production resilience is still relatively limited, and research that combines resilience with specific policy tools for systematic analysis is even more insufficient.

2.2. Agricultural Insurance and Grain Production Resilience

Agricultural insurance is generally viewed as a market-based risk-sharing mechanism that can, to some extent, reduce the production uncertainty faced by farmers and stabilize their expected returns [14,16,26–28]. Existing research indicates that the role of agricultural insurance is not limited to post-disaster compensation but extends throughout different stages of agricultural production. First, before a shock occurs, agricultural insurance can influence farmers' ex-ante production decisions by reducing effective risk exposure. Hennessy [14] theoretically pointed out that the "insurance effect" included in income support can improve farmers' optimal input levels by reducing effective risk, meaning that agricultural insurance may influence production behavior before a shock occurs. Cole and Xiong [26] further emphasize from a development economics perspective that the importance of agricultural insurance lies not only in compensating for existing losses but also in encouraging farmers to make high-yield investments and reducing their reliance on inefficient coping strategies by transferring some income risk from household asset portfolios. Consistent with this, Karlan et al. [16], based on a randomized controlled trial in northern Ghana, found that agricultural insurance significantly increased farmers' agricultural investment scale and risk-taking willingness, and pointed out that the key factor restricting agricultural investment was not insufficient credit, but risks not covered by insurance.

Besides ex-ante incentives, agricultural insurance plays a crucial role in the recovery phase following a shock. Janzen and Carter [27] found that microinsurance, after a drought shock, can reduce farmers' adoption of two costly coping strategies: selling assets to smooth consumption and cutting consumption to preserve assets, thus helping to maintain post-disaster production capacity. Similarly, Stoeffler et al. [28]'s research in Burkina Faso showed that index insurance has significant spillover effects on other agricultural investments, and its payout mechanism further demonstrates its potential as a risk management tool. Overall, these studies indicate that agricultural insurance enhances the resilience of grain production primarily through three interconnected mechanisms: sharing downside risk before a shock, stabilizing expectations and investment incentives during production, and alleviating liquidity constraints and asset stress after a disaster, thereby improving the sustainability and resilience of agricultural production. Meanwhile, a growing body of empirical research indicates that while agricultural insurance can enhance farmers' ability to cope with climate risks, its role as an adaptation tool remains significantly limited [29,30]. For example, Jensen et al. [29] found that in northern Kenya, although index insurance can reduce the risk of widespread covariance shocks faced by farmers, a considerable portion of actual losses remains uncovered due to basis risk. King and Singh [30] further pointed out that in Vietnam, farmers generally underestimate the value of agricultural index insurance, and this low demand largely stems from basis risk and a lack of trust in insurance institutions. Therefore, agricultural insurance primarily enhances resilience by stabilizing expectations, promoting investment, and alleviating post-disaster financial pressure, but its actual effectiveness largely depends on the quality of contract design, the credibility of payouts, and the implementation of the system. It can be inferred that agricultural insurance has strong advantages in risk transfer and income smoothing, but its ability to directly improve the timeliness of field operations under climate shocks is relatively limited. This also explains, to some extent, that relying solely on insurance is insufficient to constitute an adequate climate adaptation strategy.

2.3. Farmland Infrastructure and Grain Production Resilience

Existing research generally agrees that farmland infrastructure, as an important upfront investment in agricultural production, plays a fundamental role in mitigating climate shocks and stabilizing grain production [17,18,31–33]. In general, its role is mainly reflected in improving irrigation and water supply conditions, alleviating natural resource constraints, improving resource allocation efficiency, and to some extent reducing the intensity of climate shock transmission to agricultural production systems. Specifically, Siebert et al. [17] demonstrated through constructing global irrigation distribution data that irrigation facilities can alleviate the constraints of insufficient precipitation on crop growth, thereby enhancing agriculture's adaptability to climate uncertainty. Fuglie [18] pointed out from a long-term productivity perspective that agricultural infrastructure investment is one of the important factors driving sustained growth in agricultural productivity and can indirectly enhance the stability of agricultural systems by improving resource allocation and promoting technology diffusion. You et al. [31] further illustrated based on an assessment of global irrigation potential that irrigation expansion has the potential to enhance agricultural productivity in areas with corresponding natural and economic conditions. Meanwhile, Zhang and Cai [32] pointed out that climate change may exacerbate the global agricultural water deficit, further highlighting the importance of irrigation and related water infrastructure in agricultural adaptation.

However, existing research also shows that the role of farmland infrastructure is not equally significant in all situations. First, the effects of infrastructure often exhibit significant regional heterogeneity, and the actual effectiveness is influenced by factors such as resource endowment, institutional arrangements, and management efficiency [18,33]. Second, under extreme climate shocks, the disaster mitigation effect of infrastructure may experience diminishing marginal returns, meaning that when climate pressure continues to rise, relying solely on engineering investments is often insufficient to fully offset agricultural production risks [17]. Third, farmland infrastructure mainly functions by improving production conditions and alleviating factor constraints, but its function in post-disaster income recovery and liquidity support is relatively limited [31]. In addition, research on water resource allocation also suggests that the actual effects of infrastructure and irrigation management are not automatically achieved but may be constrained by water use behavior and the institutional environment [33]. Therefore, although farmland infrastructure has fundamental and long-term significance in addressing climate change and maintaining stable grain production, its resilience enhancement effect still depends on specific shock scenarios and supporting institutional conditions, and relying solely on infrastructure is often insufficient to constitute a complete risk response system.

2.4. The Relationship Between Agricultural Insurance and Farmland Infrastructure

Many studies have recognized that, in the context of climate risk, a single policy tool is often insufficient to adequately address the uncertainties in agricultural production. Therefore, the relationship between different risk management tools and their synergistic mechanisms have become an important topic in agricultural economics [16,19,34–36]. Agricultural insurance and farmland infrastructure represent two different risk management paths. The former mainly mitigates uncertainty through risk sharing and income smoothing, while the latter mainly plays a role by improving production conditions, alleviating resource constraints, and reducing the direct exposure of agricultural production to climate shocks. Therefore, from a mechanistic perspective, the two may complement each other, but under specific institutional environments and resource constraints, they may also exhibit a certain degree of substitutability. From the perspective of complementarity, existing research has shown that risk mitigation tools can alleviate the downside risks and financing constraints faced by farmers to a certain extent, thereby improving incentives for productive inputs and technology adoption [16,19,35,36]. Karlan et al. [16] pointed out that after risk and credit constraints are partially alleviated, farmers are more likely to adopt production inputs with potentially higher returns but also higher risks. Dercon et al. [19] showed that formal insurance arrangements can interact with other risk-sharing mechanisms, thereby affecting farmers' acceptance of risk management tools and their production decisions. Carter et al. [35] and Emerick et al. [36] further explained that when downside risks are mitigated, farmers are more willing to participate in long-term productive activities and adopt higher-yield technological paths. Skees et al. [34] also showed that exponential risk transfer tools can improve financial and investment conditions in high-risk environments to some extent, thereby providing more stable risk management support for agricultural production.

At the same time, existing research also shows that there is no always stable complementary relationship between agricultural insurance and farmland infrastructure. Under specific policy environments, fiscal constraints, and behavioral incentives, the two may also exhibit a certain degree of substitutability [20,21,37]. For example, when policy support is more focused on insurance subsidies, the allocation of public resources may be more inclined towards ex-post risk compensation, rather than simultaneously strengthening long-term infrastructure investment [21]. When fiscal resources are limited or there is a trade-off between policy objectives, budget competition and allocation substitution may also occur between different support tools [37]. Furthermore, risk transfer tools may alter how producers weigh risk and input, thereby influencing their long-term investment and input allocation choices [20].

Overall, there is no single and stable relationship between agricultural insurance and farmland infrastructure; its actual effect depends on multiple factors such as the type of climate shock, institutional environment, and resource constraints. While existing research has provided important insights from the perspectives of risk management, investment incentives, and technology adoption, a unified and systematic empirical analytical framework is still lacking regarding how the two dynamically change under different climate shock intensities. Therefore, it is necessary to further identify the interaction between agricultural insurance and farmland infrastructure within the same analytical framework and examine their differentiated performance under different climate scenarios.

2.5. Nonlinear Effects of Climate Adaptation Policies

In recent years, as the impact of climate change has deepened, more and more studies have begun to focus on the nonlinear mechanisms in agricultural climate adaptation policies. This means that policy effects do not remain stable under different shock levels, but may exhibit obvious state-dependent characteristics as climate pressure changes [6,22–25]. Overall, this research trend indicates that the response of agricultural systems to climate shocks often has significant nonlinearity and asymmetry, which also means that different adaptation policies may show significant differences under different climate scenarios.

From the perspective of the nonlinear impact of climate shocks themselves, Schlenker and Roberts [22] found based on US agricultural data that the impact of temperature on crop yield has significant nonlinear characteristics, and once a certain critical temperature range is exceeded, yield loss will accelerate significantly. Dell et al. [23] also showed that the impact of climate variables on economic activities and production performance is not nonlinearly constant but will adjust with changes in environmental conditions. Hsiang [24] further pointed out from the perspective of climate economics research methods that when analyzing the relationship between climate variables and economic outcomes, the potential nonlinear structure and its heterogeneity should be given full attention. In conjunction with agricultural adaptation behavior, Burke and Emerick [6] found that although farmers can adapt to climate change to some extent by adjusting planting structure and technology adoption, this ability to adapt may be limited under higher intensity climate pressure. Auffhammer et al. [25] also emphasized that in the economic analysis of climate change, the measurement of weather exposure and the identification of nonlinear effects are crucial, which provides important methodological insights for understanding how policy effects adjust with changes in the impact environment.

From the perspective of policy tools, the role of climate adaptation measures is not fixed, but may show obvious state-dependent characteristics as the intensity of climate shock and resource conditions change [38–40]. Specifically, Barrios et al. [38] showed, based on data from African countries, that the impact of climate shock on agricultural economy varies significantly under different natural environments and resource conditions, indicating that the external environment affects the actual performance of shock consequences. Hornbeck and Keskin [39] pointed out through their study of groundwater irrigation in the United States that the role of infrastructure in mitigating climate shock is obviously conditional, and its effectiveness is affected by water resource constraints and environmental background. Tack et al. [40] further found that irrigation can mitigate the adverse effects of high temperatures on crop yields to some extent, but this buffering effect is not constant in all situations. Overall, existing research consistently shows that the effects of climate adaptation policies are not constant in all scenarios, but rather dynamically adjust with changes in the intensity of climate shocks and resource conditions. Therefore, ignoring this nonlinear and state-dependent characteristic may underestimate the actual losses under extreme scenarios and may also obscure the differentiated effects of different policy tools under different climate conditions.

2.6. Research Gap and Hypothesis

In summary, existing literature has examined the impacts of climate shocks, agricultural insurance, and farmland infrastructure on agricultural production from multiple dimensions, but several aspects warrant further investigation.

First, existing studies mainly examine the effects of climate shocks on agricultural output levels or fluctuations, while systematic analyses of grain production resilience remain limited. Although resilience has gradually entered agricultural economics research, related empirical work is still largely based on linear frameworks and thus cannot fully capture the dynamic adjustment of agricultural systems under different shock intensities. Second, the literature often analyzes agricultural insurance and farmland infrastructure separately, with limited attention to their interaction. In particular, whether they are complementary or substitutive under climate shocks, and whether this relationship changes with shock intensity, still lacks direct and consistent empirical evidence. Third, most studies continue to rely on linear models that implicitly assume constant policy effects across climate scenarios. However, existing research shows that both climate shocks and adaptation policies may exhibit significant nonlinear and state-dependent characteristics. As a result, linear frameworks may underestimate losses under extreme scenarios and obscure the heterogeneous effects of policy tools across different shock ranges [6,22,24].

Based on these shortcomings, this paper incorporates agricultural insurance and farmland infrastructure within a unified analytical framework and treats climate shock as a state variable. Using a panel smoothed transformation regression model, it systematically examines the mechanism and dynamic changes in the effect of policy tools on grain production resilience under different climate scenarios.

Based on this, this paper proposes the following research hypotheses:

H1: Climate shocks have a significant negative impact on grain production resilience, and this impact exhibits nonlinear characteristics, becoming more pronounced under high-intensity shock scenarios.

H2: Climate adaptation policies (agricultural insurance and farmland infrastructure) can mitigate the negative impact of climate shocks on grain production resilience, but their effectiveness is significantly state-dependent, and the relationship between the two dynamically shifts between complementarity and substitution as the intensity of climate shocks changes.

3. Materials and Methods

3.1. Data Sources

The climate variables used in this paper are constructed based on ERA5 monthly reanalysis data from 1991 to 2024. Using 1991–2020 as the climate baseline period, the normal values of temperature and precipitation for each month in each province are first calculated. Then, provincial temperature and precipitation shock indicators are constructed based on the deviation of actual climate values from the normal values during the study period. Specifically, this paper spatially matches monthly gridded temperature and precipitation data with China’s provincial administrative boundaries. Based on the overlay results of gridded data and provincial boundaries, the monthly average temperature and total monthly precipitation for each province are calculated, thus forming the climate shock variables used in the empirical analysis. The ERA5 reanalysis data are sourced from the Copernicus Climate Data Store [41], and the administrative boundary data uses China's ADM1 level open boundary data provided by geoBoundaries [42], which is licensed under CC BY 4.0. This processing improves spatial comparability at the provincial level and allows the climate shock indicators to better characterize anomalous fluctuations relative to long-term climate normality.

The dependent variable in this paper is grain production resilience. Since grain production resilience is calculated using the three-year rolling coefficient of variation of grain output, it is necessary to retrospectively use grain output data since 2006 to construct the grain production resilience index for 2008–2024. This resulted in observations from 527 provinces and years. Therefore, the core analytical sample of this paper is balanced panel data covering 31 provinces in mainland China from 2008 to 2024.

The sample period for other explanatory and control variables used in the empirical analysis of this paper is also 2008–2024. Agricultural insurance variables are measured by agricultural insurance premium income in each province, with data sourced from the China Insurance Yearbook. To eliminate the impact of price changes, a deflator was constructed based on the Consumer Price Index (CPI) during data processing, converting nominal premium income to constant 2001 prices. Variables such as cultivated land area, effective irrigation rate, crop sown area, fertilizer application, total power of agricultural machinery, year-end resident population, and urban resident population are mainly sourced from the National Bureau of Statistics statistical yearbook and provincial statistical yearbooks. These data sources exhibit good inter-provincial comparability and temporal continuity, supporting the construction of a consistent long-term provincial panel database. For some monetary and scale-related variables, logarithmic transformations were performed as needed to reduce the impact of skewed distributions; for proportional variables, their original level values were retained to enhance the interpretability of the results.

3.2. Variable Definitions and Descriptive Statistics

Table 1. Variable definitions and descriptive statistics.

Variable	Description	Mean	SD	Min	Max
grain production resilience (GPR_{it})	Negative three-year rolling coefficient of variation of grain output	-0.025	0.024	-0.169	-0.001
precipitation shock ($Shock_{it}^{P}$)	Crop-area-weighted precipitation anomaly during staple-crop growing seasons. Unit: mm	-0.470	5.848	-16.517	6.409
Temperature shock ($Shock_{it}^{T}$)	Crop-area-weighted temperature anomaly during staple-crop growing seasons. Unit: ℃	0.151	1.424	-3.204	12.790
Agricultural insurance ($\ln s_{it}$)	Log of real agricultural insurance premium income	6.497	1.307	2.036	9.170
Farmland infrastructure ($Infra_{it}$)	effective irrigation rate	0.559	0.232	0.198	0.989
Agricultural mechanization ($\ln PMac_{it}$)	Log of agricultural machinery power per total crop sown area	-0.470	0.418	-1.432	0.992
Cultivated land area ($\ln Land_{it}$)	Log of cultivated land area	7.898	1.156	4.694	9.752
Labor input ($\ln Labor_{it}$)	Log of primary industry employment	6.169	1.142	2.996	7.954
Fertilizer use intensity ($\ln Fert_{it}$)	Log of fertilizer use per total crop sown area	-1.118	0.410	-2.592	-0.224

Urbanization ($Urban_{it}$)	Share of urban resident population in total resident population	0.583	0.138	0.219	0.898
Planting structure ($Struc_{it}$)	Share of grain sown area in total crop sown area	0.660	0.144	0.355	0.971

Note: The nominal insurance series is deflated to constant 2001 prices using a CPI-based price index. Logged variables are transformed as $\ln(x)$ in the estimations.

1. Dependent Variable

The dependent variable is grain production resilience (GPR_{it}), which in this study refers to the ability of grain production to remain relatively stable under external disturbances. In the crop-yield literature, temporal production stability is commonly assessed using interannual output variability, with the coefficient of variation (CV) widely used as a measure of relative instability [43,44]. In addition, resilience indicators derived directly from crop production time series also emphasize the central role of the relationship between mean production and variability [45]. Following this stability-based logic, this study defines grain production resilience for province i in year t as the negative of the three-year rolling coefficient of variation of grain output:

$$GPR_{it} = -CV_{it}^{(3)} \tag{1}$$

where

$$CV_{it}^{(3)} = \frac{sd\left(Y_{i,t-2}, Y_{i,t-1}, Y_{it}\right)}{mean\left(Y_{i,t-2}, Y_{i,t-1}, Y_{it}\right)} \tag{2}$$

and Y_{it} denotes grain output. Since a larger coefficient of variation implies greater production instability, the coefficient of variation by -1 ensures that a larger GPR_{it} value corresponds to stronger grain production resilience. In other words, values closer to zero indicate more stable grain production and hence higher resilience. Because GPR_{it} is constructed from grain output in years $t-2$, $t-1$, and t, it should be interpreted as a backward-looking rolling measure of recent production stability rather than a single-year outcome. Adjacent observations therefore share overlapping output windows and are mechanically smoother than annual grain output. Accordingly, the estimated coefficients are interpreted as the relationship between climate and policy conditions in year t and the three-year stability window ending in year t, rather than as a pure within-year effect on annual grain output alone.

2. Independent Variables

The climate–agriculture literature commonly measures agricultural weather exposure using deviations from climatological normals, growing-season aggregation, and crop-area weighting [46,47]. Following this approach, this study uses the 1991–2020 climatological baseline to construct province-year temperature and precipitation shocks, to capture both departures from long-run monthly climate conditions and cross-province differences in crop calendars and cropping structure. For each climate variable $k \in \{T, P\}$, where T denotes temperature and P denotes precipitation, let X_{itm}^{k} denote the monthly climate observation for province i, year t, and month mm. The monthly normal for province i in calendar month mm is defined as:

$$\bar{X}_{im}^{k} = \frac{1}{|B|}\sum_{t \in B} X_{itm}^{k} \tag{3}$$

where $B = \{1991, \dots, 2020\}$ and $|B| = 30$. This term represents the long run mean climate condition for a given province and calendar month. Based on this baseline, the monthly climate anomaly is measured as the deviation of the observed value from its corresponding monthly normal:

$$\tilde{X}_{itm}^{k} = X_{itm}^{k} - \bar{X}_{im}^{k} \tag{4}$$

Thus, $\tilde{X}_{itm}^{k}$ captures the extent to which temperature or precipitation in a given province-month departs from the long run climatic norm. To link climate anomalies to agricultural production conditions, the monthly anomalies are aggregated over the growing season of each crop. Let G_{ig} denote the set of growing-season months for crop g in province i, and let $|G_{ig}|$ denote the number of months in that growing season. The crop-specific climate shock is then defined as:

$$Shock_{igt}^{k} = \frac{1}{|G_{ig}|} \sum_{m \in G_{ig}} \tilde{X}_{itm}^{k} \tag{5}$$

This expression gives the average climate anomaly experienced by crop g over its full growing season in province i and year t. Because the climatic exposure of a province depends not only on crop-specific shocks but also on crop composition, the province-year climate shock is constructed as an area-weighted average across the major staple crops. Let A_{igt} denote the sown area of crop g in province i and year t. The area weight is defined as:

$$w_{igt} = \frac{A_{igt}}{\sum_{g \in \Theta} A_{igt}} \tag{6}$$

where Θ denotes the set of staple crops included in the analysis. This weight reflects the relative importance of each crop in the provincial cropping structure. The final province-year climate shock is then obtained by aggregating crop-specific growing-season shocks using these crop-area weights:

$$Shock_{it}^{k} = \sum_{g \in \Theta} w_{igt}\, Shock_{igt}^{k} \tag{7}$$

Accordingly, $Shock_{igt}^{T}$ and $Shock_{igt}^{P}$ represent the annual provincial temperature shock and precipitation shock, respectively. This construction allows the climate indicators to reflect both deviations from long run monthly climate normal values and differences in crop calendars and crop composition across provinces.

Agricultural insurance ($\ln s_{it}$) is proxied by provincial agricultural insurance income in real terms. To reduce right-skewness, the model uses the logarithmic transformation:

$$\ln s_{it} = \ln\left(\text{Real Agricultural Insurance Income}_{it}\right) \tag{8}$$

Farmland infrastructure ($Infra_{it}$) is measured by the effective irrigation rate, which captures the share of cultivated land effectively covered by irrigation facilities and represents a core dimension of agricultural infrastructure in China. This indicator is closely linked to actual production conditions and is therefore more suitable than broader infrastructure proxies for examining the resilience effects of farmland infrastructure under climate shocks. In economic terms, irrigation infrastructure relaxes water constraints in agricultural production and strengthens the capacity of farmland systems to withstand adverse climatic conditions, especially heat stress and rainfall fluctuations. Moreover, the effective irrigation rate is consistently reported in official provincial statistics, ensuring comparability across regions and over time. Formally, it is defined as:

$$Infra_{it} = \frac{\text{Effective Irrigated Area}_{it}}{\text{Cultivated } Land\ Area_{it}} \tag{9}$$

3. Control Variables

Agricultural mechanization ($\ln PMac_{it}$) is proxied by machinery power per total crop sown area, defined as:

$$\ln PMac_{it} = \ln\left(\frac{\text{Total Power of Agricultural Machinery}_{it}}{\text{Total Crop Sown Area}_{it}}\right) \tag{10}$$

Cultivated land area ($\ln Land_{it}$) is included to control for differences in provincial land endowments. The variable enters the model in logarithmic form:

$$\ln Land_{it} = \ln(\text{Cultivated Land Area}_{it}) \tag{11}$$

Labor input ($\ln Labor_{it}$) is measured by the number of employees in the primary industry and is also log-transformed:

$$\ln Labor_{it} = \ln\left(\text{Primary Industry Employment}_{it}\right) \tag{12}$$

Fertilizer use intensity ($\ln Fert_{it}$) is defined similarly as fertilizer use divided by total crop sown area:

$$\ln Fert_{it} = \ln\left(\frac{\text{Fertilizer Use}_{\text{it}}}{\text{Total Crop Sown Area}_{\text{it}}}\right) \tag{13}$$

Normalizing machinery power and fertilizer use by total crop sown area, rather than grain sown area, is deliberate. According to the National Bureau of Statistics of China, both total agricultural machinery power and fertilizer use apply not only to grain crops but also to cash crops. Therefore, dividing these inputs by total crop sown area provides a more appropriate intensity measure than dividing by grain sown area alone. Official statistics also define total crop sown area as the total planted or transplanted area of crops to be harvested within the calendar year.

Urbanization ($Urban_{it}$) is measured as the share of urban resident population in total resident population:

$$Urban_{it} = \frac{Urban\ Resident\ Population_{it}}{\text{Total Resident Population}_{it}} \tag{14}$$

This variable controls for differences in population structure and the degree of non-agricultural development across provinces, which may affect agricultural labor allocation and production conditions.

Planting structure ($Struc_{it}$), measured as the share of grain sown area in total crop sown area:

$$Struc_{it} = \frac{Grain\ Sown\ Area_{it}}{Total\ Crop\ Sown\ Area_{it}} \tag{15}$$

This variable captures the degree to which a province is oriented toward grain production rather than non-grain crops, which is important because the same level of agricultural inputs may affect grain resilience differently across crop structures.

Table 2 reports the pairwise correlation coefficients and VIF statistics for each explanatory variable. Overall, the correlation coefficients between most variables are at a moderate or low level, and no widespread and severe bivariate multicollinearity problem is observed. There is a high positive correlation between the two types of climate shock variables, but their VIF values are all low, indicating that their simultaneous inclusion in the model does not cause severe multicollinearity. The VIF values for agricultural insurance, farmland infrastructure, agricultural mechanization, fertilizer use intensity, urbanization, and planting structure are also within acceptable ranges. In contrast, the correlation between arable land area and labor input is strong, with the VIF for arable land area exceeding 10, and the VIF for labor input is also relatively high, indicating that multicollinearity in the model is mainly concentrated among a few control variables reflecting agricultural scale and resource endowment. Further robustness tests show that after removing these highly correlated control variables, the sign and significance of the coefficients of the core explanatory variables did not change substantially, indicating that multicollinearity did not significantly affect the main conclusions of this paper.

Table 2. Corrlation analysis and VIF test.

Variable	VIF	$Shock_{it}^{P}$	$Shock_{it}^{T}$	$\ln s_{it}$	$Infra_{it}$	$\ln PMac_{it}$	$\ln Land_{it}$	$\ln Labor_{it}$	$\ln Fert_{it}$	$Urban_{it}$	$Struc_{it}$
$Shock_{it}^{P}$	2.033	1									
$Shock_{it}^{T}$	2.373	0.673	1								
$\ln s_{it}$	3.528	-0.462	0.498	1							
$Infra_{it}$	2.226	-0.084	0.118	0.218	1						
$\ln PMac_{it}$	1.806	-0.078	0.145	-0.115	0.342	1					

$\ln Land_{it}$	12.291	-0.032	-0.039	0.437	-0.380	-0.348	1				
$\ln Labor_{it}$	8.361	0.015	-0.141	0.285	-0.240	-0.264	0.876	1			
$\ln Fert_{it}$	1.629	0.023	-0.067	-0.075	0.349	0.158	-0.117	0.078	1		
$Urban_{it}$	3.283	-0.246	0.276	0.275	0.449	-0.042	-0.427	-0.514	0.259	1	
$Struc_{it}$	2.053	0.041	-0.024	0.127	-0.314	0.055	0.433	0.183	-0.183	-0.064	1

3.3. Model Specification

3.3.1. Baseline Two-Way Fixed-Effects Model

The baseline empirical specification is a two-way fixed-effects panel model, where climate shock is represented by $Shock_{it}^{k}$. For $k \in \{T, P\}$, the baseline empirical specification can be written in a unified form as:

$$\begin{aligned} GPR_{it} = \beta_0 + \beta_1 Shock_{it}^{k} + \beta_2 Shock_{it}^{-k} + \beta_3 \ln s_{it} + \beta_4 Infra_{it} + \beta_5 (\ln s_{it} \times Infra_{it}) \\ + \beta_6 (Shock_{it}^{k} \times \ln s_{it}) + \beta_7 (Shock_{it}^{k} \times Infra_{it}) \\ + \beta_8 (Shock_{it}^{k} \times \ln s_{it} \times Infra_{it}) + \beta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{16}$$

where $Shock_{it}^{k}$ denotes the focal climate shock and $Shock_{it}^{-k}$ denotes the non-focal climate shock. The model is estimated twice: once for the temperature-shock specification and once for the precipitation-shock specification. In each case, the non-focal climate shock is retained as a control, while the interaction terms are constructed only for the focal shock. This design highlights the state-specific role of each type of climate stress while avoiding an overly saturated interaction structure. X_{it} is the vector of control variables, μ_i denotes province fixed effects, and λ_t denotes year fixed effects. Province fixed effects absorb time-invariant unobserved heterogeneity across provinces, while year fixed effects capture common macroeconomic, climatic, and policy shocks. Standard errors are clustered at the provincial level. Because the dependent variable is constructed from a three-year rolling window, the coefficients in the baseline model should be interpreted as capturing how climate shocks, agricultural insurance, and farmland infrastructure are associated with recent grain-production stability over the three-year window ending in year t, rather than with a purely contemporaneous annual production outcome.

3.3.2. Panel Smooth Transition Regression (PSTR) Extension

To examine whether the interaction between agricultural insurance and farmland infrastructure changes with climate stress, this study further estimates a panel smooth transition regression (PSTR) model. Unlike threshold models that impose abrupt coefficient shifts at a discrete cutoff, the PSTR framework allows coefficients to vary smoothly across different shock states. This makes it well suited to characterizing gradual nonlinear adjustment under intensifying climate stress.

Two PSTR specifications are estimated. In the temperature-shock specification, both temperature and precipitation shocks enter linearly, while temperature shock serves as the transition variable. In the precipitation-shock specification, both precipitation and temperature shocks enter linearly, while precipitation shock serves as the transition variable. In both cases, the PSTR structure is used to capture how the interaction and buffering effects of agricultural insurance and farmland infrastructure vary across different levels of climate stress. The model is specified as:

$$\begin{aligned} GPR_{it} = \alpha_0 + \alpha_1 Shock_{it}^{k} + \alpha_2 Shock_{it}^{-k} + \alpha_3 \ln s_{it} + \alpha_4 Infra_{it} + \alpha_5 (\ln s_{it} \times Infra_{it}) \\ + \alpha_6 (Shock_{it}^{k} \times \ln s_{it}) + \alpha_7 (Shock_{it}^{k} \times Infra_{it}) \\ + \alpha_8 (Shock_{it}^{k} \times \ln s_{it} \times Infra_{it}) + \theta' X_{it} \\ + [\delta_1 (\ln s_{it} \times Infra_{it}) + \delta_2 (Shock_{it}^{k} \times \ln s_{it}) + \delta_3 (Shock_{it}^{k} \times Infra_{it}) \\ + \delta_4 (Shock_{it}^{k} \times \ln s_{it} \times Infra_{it})] g(Shock_{it}^{k}; \gamma, c) + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{17}$$

where c is the location parameter and $\gamma > 0$ is the slope parameter governing the speed of transition between regimes. The transition function takes the logistic form:

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$$g\left(Shock_{it}^{k};\gamma,c\right)=\left[1+exp\left(-\gamma\left(Shock_{it}^{k}-c\right)\right)\right]^{-1},\gamma>0 \tag{18}$$

When $g\left(Shock_{it}^{k};\gamma,c\right)$ is close to 0, the model approximates a low-shock regime; when it is close to 1, it approximates a high-shock regime. Accordingly, cc should be interpreted as the location around which the transition is centered along the distribution of the focal climate shock, rather than as a sharp threshold in the threshold-regression sense.

Under this specification, α_3 and α_4 represent the direct effects of agricultural insurance and farmland infrastructure, respectively. The coefficients α_5, α_6, α_7, and α_8 capture, respectively, the low-shock interaction effect between insurance and infrastructure, the low-shock buffering effect of insurance, the low-shock buffering effect of infrastructure, and their low-shock joint buffering effect. In the high-shock regime, the corresponding effects become $\alpha_5+\delta_1$, $\alpha_6+\delta_2$, $\alpha_7+\delta_3$, and $\alpha_8+\delta_4$. Thus, a positive δ_j indicates that the corresponding effect becomes more positive, or less negative, as the system moves from the low-shock regime toward the high-shock regime; a negative δ_j implies the opposite. The economic interpretation of complementarity or substitution should therefore be based on the total regime-specific effect, rather than on the sign of δ_j alone.

Because the location parameter is not identified under the null of linearity, the linearity test is implemented through an auxiliary regression. Following the standard PSTR procedure, the transition effect is approximated by a third-order polynomial in the transition variable. Let $q_{\mathrm{it}}=Shock_{it}^{k}$. The auxiliary regression is written as:

$$GPR_{it}=\mu_i+\lambda_t+\omega^{'}Z_{it}+\sum_{v=1}^{4}\sum_{l=1}^{3}\eta_{vl}\left(W_{v,it}q_{it}^{l}\right)+u_{it} \tag{19}$$

where Z_{it} denotes the full set of regressors included in the baseline linear specification and $W_{v,it}$ denotes the regressors whose coefficients are allowed to vary with the intensity of climate shocks. Specifically, $W_{1,it}=\ln s_{it}\times Infra_{it}$, $W_{2,it}=Shock_{it}^{k}\times\ln s_{it}$, $W_{3,it}=Shock_{it}^{k}\times Infra_{it}$, $W_{4,it}=Shock_{it}^{k}\times\ln s_{it}\times Infra_{it}$. The null hypothesis of linearity is:

$$H_0:\eta_{vl}=0,\forall v=1,\ldots,4;\ l=1,2,3 \tag{20}$$

which implies that the baseline two-way fixed-effects model is sufficient and no smooth-transition structure is required. The alternative hypothesis is:

$$H_1:\exists\eta_{vl}\neq 0 \tag{21}$$

which implies that at least some coefficients vary with the intensity of climate shocks and that a nonlinear PSTR specification is more appropriate. In principle, the auxiliary regression contains $4\times 3=12$ polynomial interaction terms. However, some of these terms are perfectly collinear with regressors already included in the baseline specification and are therefore removed during the residualization and estimation procedure. In the final implementation, only nine non-collinear residualized auxiliary terms are retained for the joint test. Accordingly, the degrees of freedom of the Wald test equal 9. The province-clustered robust Wald statistic is:

$$W=\hat{\eta}^{'}[Var(\hat{\eta})]^{-1}\hat{\eta} \tag{22}$$

which asymptotically follows a chi-square distribution under the null hypothesis. The degrees of freedom equal the number of jointly tested non-collinear coefficients retained in the final auxiliary regression.

Table 3 reports the results of the linearity test. In both the temperature-shock and precipitation-shock specifications, the null hypothesis of linearity is rejected at the 1% level. This indicates that the interaction and buffering effects of agricultural insurance and farmland infrastructure on grain production resilience vary systematically with the intensity of climate shocks, thereby providing empirical support for the use of a nonlinear PSTR specification.

Table 3. Linearity tests against the linear fixed-effects model for the PSTR specification.

Item	Temperature-PSTR	Precipitation-PSTR
Transition variable	Temperature shock ($Shock_{it}^{T}$)	Precipitation shock ($Shock_{it}^{P}$)
Test statistic	35.105	55.317
Degree of freedom	9	9
p-value	< 0.001	< 0.001
Decision	Reject linearity	Reject linearity

After linearity is rejected, the number of transition functions is determined sequentially using the following general PSTR specification:

$$GPR_{it} = \mu_i + \lambda_t + \omega' Z_{it} + \sum_{h=1}^{r} \xi_h' W_{it} g_h(Shock_{it}^{k}; \gamma_h, c_h) + u_{it}, \tag{23}$$

where r denotes the number of transition functions, W_{it} is the vector of regressors whose coefficients are allowed to vary with climate stress, $Shock_{it}^{k}$ is the transition variable, γ_h is the slope parameter, and c_h is the location parameter of the h-th transition function. For identification, the location parameters are ordered as $c_1 < c_2 < \ldots < c_r$. In this paper, each transition function takes the logistic form:

$$g\left(Shock_{it}^{k}; \gamma_h, c_h\right) = \left[1 + exp\left(-\gamma_h\left(Shock_{it}^{k} - c_h\right)\right)\right]^{-1}, \gamma > 0 \tag{24}$$

For a given number of transition functions r, the unknown parameters are estimated by nonlinear least squares:

$$(\hat{\gamma}, \hat{c}) = arg\,\min_{\gamma, c} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[GPR_{it} - \widehat{GPR}_{it}(\gamma, c)\right]^2, \tag{25}$$

where $\hat{\gamma} = (\hat{\gamma}_1, \ldots, \hat{\gamma}_r)$ and $\hat{c} = (\hat{c}_1, \ldots, \hat{c}_r)$. To determine whether an additional transition function is needed, a sequential test of no remaining nonlinearity is conducted after estimating the model with r transition functions. The null and alternative hypotheses are H_0: the model with r transition functions are sufficient, H_1: the model requires $r + 1$ transition functions. Accordingly, the optimal number of transition functions is selected as:

$$\hat{r} = min\left\{r \geq 1: H_0^{(r)}\ is\ not\ rejected\right\} \tag{26}$$

Transition functions are added one by one until the null hypothesis of no remaining nonlinearity can no longer be rejected. Conditional on the selected $\hat{r}$, the estimated location parameters are given by $\hat{c} = (\hat{c}_1, \hat{c}_2, \ldots, \hat{c}_{\hat{r}})$. If the transition variable is standardized before estimation, the corresponding raw location value can be recovered as:

$$\hat{c}_h^{raw} = \bar{q} + s_q \hat{c}_h^{std} \tag{27}$$

where $\bar{q}$ and s_q denote the sample mean and standard deviation of the original transition variable, respectively.

Table 4 shows that, regardless of whether temperature impact or precipitation impact is used as the transformation variable, the optimal number of transition functions is 1. The criterion is the BIC criterion: in both models, the BIC values for $r = 1$ are -4294.18 and -4287.428 respectively, both lower than the corresponding values for $r = 2$ and $r = 3$. This indicates that, considering both model fit and parameter simplicity, a single transition function is optimal. Therefore, this paper ultimately adopts a PSTR model with a single transition function rather than a multiple-transition specification.

Table 4. Selection of the Optimal Number of Transition Functions.

Transition Variable	Number of Transition Functions (r)	BIC	Sd location parameter	Raw location parameter
Temperature shock	1	**-4294.18**	0.5737	2.8685
Temperature shock	2	-4269.888	0.4828, 0.4837	2.3388, 2.3444
Temperature shock	3	-4239.196	-1.5530, -0.7274, 0.4693	-9.5219, -4.7121, 2.2601
Precipitation shock	1	**-4287.428**	1.1042	1.6719
Precipitation shock	2	-4268.199	0.7892, 0.8357	1.2371, 1.3014
Precipitation shock	3	-4241.888	-0.4528, 0.4134, 0.4164	-0.4769, 0.7185, 0.7227

Table 5 reports the sequential tests for adding further transition functions to the PSTR model. Since all p-values are above the 10% significance level, neither the temperature-shock specification nor the precipitation-shock specification provides sufficient evidence to support an additional transition function. This indicates that a single transition function is sufficient to capture the main state-dependent nonlinear pattern in the data. Together with the BIC results in Table 4, these findings support the final specification of a one-transition-function PSTR model.

Table 5. Sequential Model Comparison for Additional Transition Functions.

Model	From r	To $r+1$	LR Statistic	p-value
Temperature-shock PSTR	1	2	10.3113	0.1121
Temperature-shock PSTR	2	3	6.9108	0.3292
Precipitation-shock PSTR	1	2	8.3736	0.2120
Precipitation-shock PSTR	2	3	5.2929	0.5068

4. Results

4.1. Empirical Results

Before interpreting the individual regression coefficients, it is useful to summarize the transition structure identified by the PSTR model and the implied regime-specific effects. Table 6 reports the estimated transition speed, location parameter, and regime-specific interaction and marginal effects under the low-shock and high-shock regimes. The two specifications display markedly different transition patterns. In the temperature-shock specification, the estimated transition speed is relatively high ($\gamma = 20$), indicating a relatively steep change in the transition function around the estimated location parameter. The standardized location parameter is 0.5737, corresponding to a raw value of 2.8685, which suggests that the model moves relatively quickly from the low-temperature-shock regime toward the high-temperature-shock regime around this level of temperature stress. By contrast, the precipitation-shock specification yields a much lower transition speed ($\gamma = 0.5$), indicating a smoother and more gradual regime adjustment. Its standardized location parameter is 1.1042, corresponding to a raw value of 1.6719, which implies that the effects of precipitation shocks evolve more gradually across regimes.

Table 6. Estimated transition parameters and implied regime-specific effects in the PSTR models.

Model	Effect	Transition speed γ	Sd location parameter	Raw location parameter	Low-shock regime	High-shock regime
Temperature-PSTR	Interaction effect ($\ln s_{it} \times Infra_{it}$)	20	0.5737	2.8685	-0.0329	-0.0295
Temperature-PSTR	Marginal Effect of $\ln s_{it}$	20	0.5737	2.8685	-0.0024	-0.001

Temperature-PSTR	Marginal Effect of $Infra_{it}$	20	0.5737	2.8685	0.0212	0.0619
Precipitation-PSTR	Interaction effect $(\ln s_{it} \times Infra_{it})$	0.5	1.1042	1.6719	-0.0901	0.1066
Precipitation-PSTR	Marginal Effect of $\ln s_{it}$	0.5	1.1042	1.6719	-0.0331	0.0537
Precipitation-PSTR	Marginal Effect of $Infra_{it}$	0.5	1.1042	1.6719	-0.4203	0.8399

Note: Low-shock and high-shock regimes are defined by the estimated PSTR transition function. The reported regime-specific interaction effects and marginal effects are evaluated from the estimated coefficients, with the transition function approximated at the low-shock regime ($g \approx 0$) and high-shock regime ($g \approx 1$).

The regime-specific effects also reveal different adjustment patterns under the two types of climate shocks. In the temperature-shock specification, the marginal effect of agricultural insurance remains close to zero and slightly negative in both regimes, changing only from -0.0024 to -0.0010. By contrast, the marginal effect of farmland infrastructure remains positive in both regimes and rises from 0.0212 in the low-shock regime to 0.0619 in the high-shock regime. This suggests that as temperature stress intensifies, the contribution of farmland infrastructure to grain production resilience becomes more pronounced, whereas the direct contribution of agricultural insurance remains limited. At the same time, the interaction effect between agricultural insurance and farmland infrastructure is negative in both regimes (-0.0329 and -0.0295, respectively), indicating a more substitutive pattern than a complementary one, although the degree of substitution appears to weaken slightly under stronger temperature shocks. In other words, under rising temperature stress, resilience improvement seems to rely more on farmland infrastructure itself than on additional gains from combining insurance with infrastructure.

The precipitation-shock specification shows a different pattern. In the low-shock regime, the marginal effects of agricultural insurance and farmland infrastructure, as well as their interaction effect, are all negative (-0.0331, -0.4203, and -0.0901, respectively). Once the model moves into the high-shock regime, however, all three effects become positive: the marginal effect of agricultural insurance rises to 0.0537, the marginal effect of farmland infrastructure rises to 0.8399, and the interaction effect increases to 0.1066. This suggests that under stronger precipitation shocks, agricultural insurance and farmland infrastructure not only become more effective individually but may also generate additional resilience gains when used together. Overall, these results indicate that the relationship between agricultural insurance and farmland infrastructure differs by the type of climate shock: under temperature shocks, they display a more substitutive pattern, whereas under stronger precipitation shocks, they tend to exhibit a more complementary pattern.

Before explaining the specific coefficients, it's important to emphasize a general conclusion: compared to the linear two-way fixed effects model, the two PSTR models have lower BIC values, -2513.481 and -2509.609 respectively, while the corresponding fixed effects models have BIC values of -2463.066 and -2455.051. This indicates that, allowing the correlation coefficients to vary smoothly with the level of climate shock, the PSTR models achieve a better balance between goodness of fit and model parsimony. In other words, the relationship between grain production resilience and climate shock, agricultural insurance, and farmland infrastructure is not constant under all climatic conditions but exhibits significant state dependence and nonlinear adjustment characteristics.

From the perspective of the impact of climate shock itself, both PSTR results show that both temperature shock and precipitation shock weaken grain production resilience. In the Temperature-PSTR model, the coefficients for precipitation shock and temperature shock are -0.0021 and -0.0101, respectively, both significant at the 5% level. In the Precipitation-PSTR model, these coefficients are -0.0015 and -0.0405, respectively, also significantly negative. This indicates that both abnormally high temperatures and abnormal precipitation weaken the ability of the grain production system to maintain stable output, absorb risks, and restore production capacity. In contrast, the linear fixed effects model can also identify some negative shocks in an average sense, but its identification strength is relatively weak. This suggests that the linear model can capture some average effects, while the PSTR model is better able to reveal that the impact of climate shocks adjusts nonlinearly with changes in risk status.

From the perspective of the policy variables themselves, the direct promoting effect of agricultural insurance is relatively weak and unstable, while the positive effect of farmland infrastructure is more robust. Agricultural insurance only shows a significant positive value (0.0127) in the Temperature-PSTR model and is not significant in the other three models. This indicates that agricultural insurance does not have a universal and stable direct effect on improving grain production resilience; its effect is more dependent on specific shock scenarios. In contrast, farmland infrastructure exerts a more stable positive effect, with larger coefficients in the two PSTR models. This suggests that farmland infrastructure has a more stable effect on improving grain production resilience. In economic terms, infrastructure can directly enhance the material basis for agricultural production systems to resist and absorb climate shocks by improving irrigation, drainage, and farmland engineering conditions; while agricultural insurance plays a greater role through income compensation, risk sharing, and mitigating post-disaster reproduction constraints. Therefore, its individual effect is often less direct and stable than that of infrastructure.

It is particularly important to note that the relationship between agricultural insurance and farmland infrastructure cannot be judged solely based on the coefficient of a single interaction term but should be interpreted in conjunction with the state-specific effects reported in Table 6. From the perspective of average or low-shock states, the interaction term between insurance and infrastructure is generally negative in all models, indicating that they tend to exhibit a substitution relationship rather than a simple linear complementary relationship under normal circumstances. The economic implication is that regions with better infrastructure have already mitigated some climate exposure through irrigation and field engineering, thus their reliance on the marginal protection function of insurance is relatively low. In contrast, in regions with relatively weak infrastructure, insurance is more likely to play a supplementary risk-sharing role. In other words, while both policy tools serve agricultural risk management, their mechanisms of action differ, and there is some functional overlap. However, the PSTR results further indicate that this substitution relationship is not fixed but adjusts with changes in the type and intensity of the shock.

Regarding the temperature shock path, the results suggest that both agricultural insurance and farmland infrastructure provide some buffering effect under low-shock conditions, although infrastructure is more robust. As shown in Table 6, the state-specific marginal effect of agricultural insurance is close to zero and slightly negative in both states, whereas that of farmland infrastructure is positive in both states and stronger under high-shock conditions. At the same time, the interaction effect between insurance and infrastructure is negative in both states, indicating an overall substitutive relationship under temperature shocks. Although this substitutability weakens somewhat as temperature shocks intensify, it does not turn into a significant complementary relationship. This suggests that under rising temperature pressure, grain production resilience depends more on farmland infrastructure itself than on additional synergy between insurance and infrastructure.

In contrast, the precipitation shock path shows stronger nonlinearity and state dependence. As reported in Table 6, under low precipitation shock conditions, agricultural insurance, farmland infrastructure, and their interaction effects are all negative, but they all become positive once the model enters a high-shock state. This suggests that under stronger precipitation shocks, the individual effects of insurance and infrastructure are both strengthened, and their joint use may generate additional resilience gains. In other words, under heavy precipitation, waterlogging, or high drainage pressure, infrastructure alone is insufficient to offset risks sustainably, making insurance increasingly important and shifting the relationship between the two tools from a substitutive tendency under low shocks to a more complementary one under high shocks.

Overall, Table 7 delivers three main messages. First, the effect of climate shocks on grain production resilience is significantly nonlinear and state-dependent, so linear fixed-effects models capture only average effects and cannot fully reflect the underlying adjustment mechanism. Second, compared with agricultural insurance, farmland infrastructure shows a more stable and direct resilience-enhancing effect. Third, there is no fixed synergistic relationship between agricultural insurance and farmland infrastructure: under temperature shocks, they tend to be more substitutive, whereas under strong precipitation shocks, they are more likely to be complementary. Therefore, improving grain production resilience requires not a single policy tool, but more targeted policy combinations based on the type and intensity of climate risks.

Table 7. PSTR and Fixed-effects Results for Grain Production Resilience.

Variables	Temperature-PSTR	Precipitation - PSTR	Temperature FE	Precipitation FE
precipitation shock ($Shock_{it}^{P}$)	-0.0021** (0.0009)	-0.0015*** (0.0004)	-0.0012 (0.0008)	-0.017* (0.0086)
Temperature shock ($Shock_{it}^{T}$)	-0.0101** (0.0039)	-0.0405** (0.0175)	-0.0008 (0.0019)	-0.0016*** (0.0004)
Agricultural insurance ($\ln s_{it}$)	0.0127* (0.0069)	0.0079 (0.0059)	0.0020 (0.0041)	0.0046 (0.0043)
farmland infrastructure ($Infra_{it}$)	0.2450*** (0.0836)	0.1667** (0.0687)	0.0574* (0.0313)	0.0516** (0.0230)
$\ln s_{it} \times Infra_{it}$	-0.0348*** (0.0123)	-0.0898*** (0.0242)	-0.0079* (0.0044)	-0.0066** (0.0031)
$Shock_{it}^{k} \times \ln s_{it}$	0.0018** (0.0007)	-0.0133*** (0.0031)	0.0004 (0.0003)	-0.0033** (0.0012)
$Shock_{it}^{k} \times Infra_{it}$	0.0214** (0.0080)	-0.0105 (0.0392)	0.0061** (0.0029)	-0.0242** (0.0107)
$Shock_{it}^{k} \times \ln s_{it} \times Infra_{it}$	-0.0040*** (0.0014)	-0.0065* (0.0033)	-0.0012** (0.0005)	-0.0048** (0.0018)
Agricultural mechanization ($\ln PMac_{it}$)	-0.0024 (0.0079)	-0.0015 (0.0092)	0.0078 (0.0173)	0.0129 (0.0186)
Cultivated land area ($\ln Land_{it}$)	0.0114 (0.0153)	0.0164 (0.0147)	0.0090 (0.0099)	0.0048 (0.0108)
Labor input ($\ln Labor_{it}$)	-0.0090 (0.0086)	-0.0064 (0.0092)	-0.0006 (0.0091)	-0.0004 (0.0089)
Fertilizer use intensity ($\ln Fert_{it}$)	0.0305** (0.0143)	0.0368*** (0.0132)	0.0333** (0.0143)	0.0355** (0.0130)
Urbanization ($Urban_{it}$)	-0.0612 (0.0459)	-0.0330 (0.0495)	-0.0280 (0.0533)	-0.0099 (0.0595)
Planting structure ($Struc_{it}$)	-0.0272 (0.0355)	-0.0285 (0.0418)	-0.0283 (0.0389)	-0.0239 (0.0450)
$\ln s_{it} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0051 (0.0052)	0.1966*** (0.0607)	-	-
$Shock_{it}^{k} \times \ln s_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0002 (0.0005)	0.0112** (0.0053)	-	-
$Shock_{it}^{k} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	-0.0390*** (0.0086)	-0.1210*** (0.0406)	-	-
$Shock_{it}^{k} \times \ln s_{it} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0036** (0.0017)	0.0001 (0.0109)	-	-
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
BIC	**-2513.481**	-2509.609	-2463.066	-2455.051

Note: () reports standard errors. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

4.2. Robustness Test

4.2.1. Sensitivity to Omitted Controls in the PSTR Model

From a robustness perspective, Table 8 shows that the main conclusions of the PSTR model remain generally consistent under both settings of retaining and removing control variables, although the magnitude and significance of some coefficients change somewhat. This indicates that the core empirical findings in this paper are not mechanically driven by specific control variable settings, but different combinations of control variables still affect the strength of local estimation results to some extent.

Table 8. PSTR and Fixed-effects Results for Grain Production Resilience.

Variables	Temperature-PSTR with controls	Temperature-PSTR without controls	Precipitation - PSTR with controls	Precipitation - PSTR without controls
Transition speed γ	20	20	0.5	0.5
location parameter	2.8685	2.6372	1.6719	1.6719
precipitation shock ($Shock_{it}^{P}$)	-0.0021** (0.0009)	-0.0095** (0.0042)	-0.0015*** (0.0004)	-0.0344* (0.0183)
Temperature shock ($Shock_{it}^{T}$)	-0.0101** (0.0039)	-0.0014* (0.0007)	-0.0405** (0.0175)	-0.0013*** (0.0003)
Agricultural insurance ($\ln s_{it}$)	0.0127* (0.0069)	0.0114 (0.0072)	0.0079 (0.0059)	0.0070 (0.0058)
farmland infrastructure ($Infra_{it}$)	0.2450*** (0.0836)	0.2369** (0.0898)	0.1667** (0.0687)	0.1416* (0.0823)
$\ln s_{it} \times Infra_{it}$	-0.0348*** (0.0123)	-0.0400*** (0.0125)	-0.0898*** (0.0242)	-0.0853*** (0.0246)
$Shock_{it}^{k} \times \ln s_{it}$	0.0018** (0.0007)	0.0017** (0.0008)	-0.0133*** (0.0031)	-0.0128*** (0.0034)
$Shock_{it}^{k} \times Infra_{it}$	0.0214** (0.0080)	0.0219** (0.0091)	-0.0105 (0.0392)	0.0050 (0.0500)
$Shock_{it}^{k} \times \ln s_{it} \times Infra_{it}$	-0.0040*** (0.0014)	-0.0041** (0.0016)	-0.0020 (0.0044)	-0.0021 (0.0052)
Agricultural mechanization ($\ln PMac_{it}$)	-0.0024 (0.0079)	-	-0.0015 (0.0092)	-
Cultivated land area ($\ln Land_{it}$)	0.0114 (0.0153)	-	0.0164 (0.0147)	-
Labor input ($\ln Labor_{it}$)	-0.0090 (0.0086)	-	-0.0064 (0.0092)	-
Fertilizer use intensity ($\ln Fert_{it}$)	0.0305** (0.0143)	-	0.0368*** (0.0132)	-
Urbanization ($Urban_{it}$)	-0.0612 (0.0459)	-	-0.0330 (0.0495)	-
Planting structure ($Struc_{it}$)	-0.0272 (0.0355)	-	-0.0285 (0.0418)	-
$\ln s_{it} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0051 (0.0052)	0.0027 (0.0044)	0.1966*** (0.0607)	0.1765*** (0.0626)
$Shock_{it}^{k} \times \ln s_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0002 (0.0005)	0.0001 (0.0005)	0.0112** (0.0053)	0.0116** (0.0051)
$Shock_{it}^{k} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	-0.0390*** (0.0086)	-0.0439*** (0.0081)	-0.1210*** (0.0406)	-0.1217*** (0.0410)
$Shock_{it}^{k} \times \ln s_{it} \times Infra_{it} \times g(Shock_{it}^{k}; \gamma, c)$	0.0036** (0.0017)	0.0054*** (0.0016)	0.0001 (0.0109)	-0.0007 (0.0089)
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
BIC	-2513.481	-2534.028	-2509.609	-2524.77

Note: () reports standard errors. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

First, the nonlinear transformation structure of the model is generally stable. In the temperature shock PSTR model, the transformation velocity parameter γ is 20 under both settings, and the original value of the location parameter is only slightly adjusted from 2.8685 to 2.6372; in the precipitation shock PSTR model, γ and the location parameter are stable at 0.5 and 1.6719 under the two settings, respectively. Overall, this shows that the state-dependent nonlinear transformation pattern identified by the model does not change substantially under different settings of including or not including control variables.

Second, the directions of the core variables remain generally consistent. Regardless of whether control variables were included, the signs of the climate shock terms in both models remained unchanged, and most remained statistically significant, indicating that the fundamental conclusion that climate shocks weaken grain production resilience is highly stable. Meanwhile, the farmland infrastructure coefficient remained positive in all four PSTR settings, suggesting that its promoting effect on grain production resilience is generally robust. The basic interaction term between agricultural insurance and farmland infrastructure was also negative in all four settings, indicating that under average or low-impact conditions, there is no unconditional and stable synergistic relationship between the two, but rather a tendency towards substitution. However, it should be noted that the significance and magnitude of individual coefficients changed after removing control variables; therefore, a more accurate conclusion should be understood as the main interaction patterns being generally preserved, rather than all local effects remaining completely unchanged under different settings.

Furthermore, the temperature shock model exhibited relatively stronger robustness. In the Temperature-PSTR, several key interaction terms related to state dependence maintained the same sign under both settings with and without control variables, and most remained significant. For example, the expression $Shock_{it}^{k} \times Infra_{it} \times g\left(Shock_{it}^{k}; \gamma, c\right)$ is significantly negative under both settings, and the four-fold interaction terms remain positive and significant. This indicates that under temperature shock scenarios, the state-dependent regulation structure identified by the model does not disappear due to the removal of control variables, and the related nonlinear interaction patterns are generally stable.

In contrast, while the precipitation shock model maintains a consistent overall direction, it is more sensitive to the setting of control variables. In Precipitation-PSTR, the significance of some core terms and interaction terms weakens after removing control variables, but the main direction remains unchanged. In particular, $Shock_{it}^{k} \times \ln s_{it} \times g\left(Shock_{it}^{k}; \gamma, c\right)$ is significantly positive in both settings, while $Shock_{it}^{k} \times Infra_{it} \times g\left(Shock_{it}^{k}; \gamma, c\right)$ is also significantly negative in both settings, and the coefficients are quite similar. This indicates that the state heterogeneity identified in the precipitation impact model did not disappear due to the omission of control variables.

Overall, Table 8 shows that after removing control variables, the main state-dependent transformation structure, core variable orientations, and most key interactions of the PSTR model did not fundamentally change. Therefore, the baseline results are generally robust. However, this robustness should be understood as the stability of core conclusions and main interaction patterns, rather than the complete consistency of all coefficient values and significance under different settings.

4.2.2. Alternative Estimators and Endogeneity Checks

Given that grain production resilience is constructed as the negative three-year rolling coefficient of variation of grain output, introducing a lagged dependent variable may mechanically amplify persistence because adjacent observations share overlapping output windows. Therefore, instead of relying on dynamic GMM estimators, this study employs a set of robustness and endogeneity-related checks that are more consistent with the structure of the dependent variable. Unless otherwise noted, the analysis in this subsection is based on the same linear interaction specification as the baseline model.

First, the baseline specification is re-estimated with Driscoll-Kraay standard errors. Because this procedure does not alter the estimating equation itself, it should be understood as an alternative inference approach rather than a different estimator.

Second, to mitigate simultaneity and reverse-causality concerns, the policy variables and their interaction terms are replaced with their one-period lags, while the climate shocks remain contemporaneous:

$$\begin{aligned} GPR_{it} = {} & \beta_0 + \beta_1 Shock_{it}^{k} + \beta_2 Shock_{it}^{-k} + \beta_3 \ln s_{i,t-1} + \beta_4 Infra_{i,t-1} \\ & + \beta_5\left(\ln s_{i,t-1} \times Infra_{i,t-1}\right) + \beta_6\left(Shock_{it}^{k} \times \ln s_{i,t-1}\right) \\ & + \beta_7\left(Shock_{it}^{k} \times Infra_{i,t-1}\right) + \beta_8\left(Shock_{it}^{k} \times \ln s_{i,t-1} \times Infra_{i,t-1}\right) + \beta' X_{it} \\ & + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{28}$$

This approach preserves the contemporaneous timing of climate shocks while allowing the policy variables to precede the outcome variable temporally, thereby reducing concerns that current grain production resilience may simultaneously affect current insurance and infrastructure conditions.

As a further timing-based placebo check, the contemporaneous policy variables are also replaced with their one-period leads:

$$\begin{aligned} GPR_{it} = {} & \beta_0 + \beta_1 Shock_{it}^{k} + \beta_2 Shock_{it}^{-k} + \beta_3 \ln s_{i,t+1} + \beta_4 Infra_{i,t+1} \\ & + \beta_5\left(\ln s_{i,t+1} \times Infra_{i,t+1}\right) + \beta_6\left(Shock_{it}^{k} \times \ln s_{i,t+1}\right) \\ & + \beta_7\left(Shock_{it}^{k} \times Infra_{i,t+1}\right) + \beta_8\left(Shock_{it}^{k} \times \ln s_{i,t+1} \times Infra_{i,t+1}\right) + \beta' X_{it} \\ & + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{29}$$

If future policy variables do not significantly explain current grain production resilience, this provides additional evidence that the baseline relationship is less likely to be driven by simple reverse causality or spurious anticipatory trends.

Table 9 shows that, under the temperature-shock specification, the main climate-shock coefficient and several key interaction terms remain qualitatively stable after applying Driscoll-Kraay standard errors, replacing policy variables with one-period lags, and conducting the lead-placebo exercise. At the same time, the magnitude and significance of some policy-related coefficients vary across columns, especially in the placebo-lead specification. These results suggest that the main interaction pattern under the temperature-shock specification is reasonably robust, although the lead test does not fully rule out timing-related concerns.

Table 9. Alternative Estimators and Endogeneity-Related Checks: Temperature-Shock Specification.

Variables	DK SE	Lagged policy variables	Placebo lead test
Temperature shock	-0.0107*** (0.0021)	-0.0081*** (0.0025)	-0.0121** (0.0050)
precipitation shock	-0.0011 (0.0008)	-0.0003 (0.0016)	-0.0014 (0.0009)
Agricultural insurance	0.0122** (0.0050)	0.0181** (0.0086)	0.0100 (0.0063)
Farmland infrastructure	0.1610** (0.0674)	0.2252** (0.1067)	0.2408** (0.0904)
Insurance × Infrastructure	-0.0217* (0.0106)	-0.0312* (0.0155)	-0.0254** (0.0116)
Shock × Insurance	0.0019*** (0.0003)	0.0015** (0.0006)	0.0020** (0.0009)
Shock × Infrastructure	0.0172*** (0.0047)	0.0111** (0.0050)	0.0207* (0.0108)
Shock × Insurance × Infrastructure	-0.0035*** (0.0006)	-0.0024** (0.0012)	-0.0039** (0.0018)
Agricultural mechanization	-0.0001 (0.0064)	-0.0044 (0.0096)	-0.0016 (0.0079)
Cultivated land area	0.0122 (0.0097)	0.0164 (0.0171)	0.0187 (0.0132)
Labor input	-0.0097 (0.0072)	-0.0023 (0.0097)	-0.0167 (0.0101)
Fertilizer use intensity	0.0320*** (0.0087)	0.0347* (0.0180)	0.0311** (0.0151)
Urbanization	-0.0494 (0.0575)	-0.1104 (0.0693)	-0.0475 (0.0668)
Planting structure	-0.0337 (0.0197)	-0.0019 (0.0417)	-0.0527 (0.0440)
Province fixed effects	Yes	Yes	Yes

Year fixed effects	Yes	Yes	Yes

Note: () reports standard errors. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 10 provides similar but somewhat weaker evidence for the precipitation-shock specification. The negative effects of precipitation shock and temperature shock remain stable in sign, and several key interaction terms preserve their underlying direction across checks. However, the significance of some policy-related coefficients changes across columns, indicating that the precipitation-shock specification is somewhat more sensitive to alternative timing assumptions and inference procedures. Overall, the results support the broad qualitative pattern of the baseline findings, while suggesting that endogeneity-related concerns cannot be completely dismissed.

Table 10. Alternative Estimators and Endogeneity-Related Checks: Precipitation -Shock Specification.

Variables	DK SE	Lagged policy variables	Placebo lead test
Temperature shock	-0.0306** (0.0128)	-0.0343** (0.0157)	-0.0302* (0.0152)
precipitation shock	-0.0017*** (0.0004)	-0.0017** (0.0007)	-0.0020*** (0.0004)
Agricultural insurance	0.0078 (0.0062)	0.0146* (0.0083)	0.0054 (0.0037)
Farmland infrastructure	0.1580 (0.0931)	0.2301** (0.1010)	0.2193** (0.0839)
Insurance × Infrastructure	-0.0197 (0.0129)	-0.0300** (0.0140)	-0.0217** (0.0106)
Shock × Insurance	-0.0061*** (0.0020)	-0.0067** (0.0031)	-0.0058** (0.0028)
Shock × Infrastructure	-0.0727** (0.0315)	-0.0802** (0.0350)	-0.0686* (0.0363)
Shock × Insurance × Infrastructure	-0.0145*** (0.0046)	-0.0155** (0.0064)	-0.0133** (0.0060)
Agricultural mechanization	-0.0002 (0.0065)	-0.0037 (0.0096)	-0.0021 (0.0081)
Cultivated land area	0.0183 (0.0105)	0.0191 (0.0179)	0.0223 (0.0134)
Labor input	-0.0055 (0.0077)	0.0001 (0.0103)	-0.0134 (0.0105)
Fertilizer use intensity	0.0348*** (0.0077)	0.0374** (0.0171)	0.0322** (0.0146)
Urbanization	-0.0324 (0.0527)	-0.0768 (0.0727)	-0.0476 (0.0727)
Planting structure	-0.0313* (0.0150)	-0.0098 (0.0441)	-0.0456 (0.0458)
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: () reports standard errors. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

4.2.3. Window-Aligned Specification

As an additional timing-consistency check, the core explanatory variables are redefined as three-year rolling averages aligned with the construction window of GPR_{it}t. Specifically, for each variable Z_{it}, the aligned measure is defined as $\bar{Z}_{\mathrm{it}}^{(3)} = \left(Z_{it} + Z_{i,t-1} + Z_{i,t-2}\right)/3$. The model is then re-estimated using window-aligned policy and climate variables as:

$$\begin{aligned} GPR_{it} = \beta_0 &+ \beta_1 \overline{Shock_{it}^{k}}^{(3)} + \beta_2 \overline{Shock_{it}^{-k}}^{(3)} + \beta_3 \overline{\ln s_{it}}^{(3)} + \beta_4 \overline{Infra_{it}}^{(3)} \\ &+ \beta_5 \left(\overline{\ln s_{it}}^{(3)} \times \overline{Infra_{it}}^{(3)}\right) + \beta_6 \left(\overline{Shock_{it}^{k}}^{(3)} \times \overline{\ln s_{it}}^{(3)}\right) \\ &+ \beta_7 \left(\overline{Shock_{it}^{k}}^{(3)} \times \overline{Infra_{it}}^{(3)}\right) + \beta_8 \left(\overline{Shock_{it}^{k}}^{(3)} \times \overline{\ln s_{it}}^{(3)} \times \overline{Infra_{it}}^{(3)}\right) \\ &+ \beta^{'} X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (30)$$

This specification addresses the concern that the dependent variable reflects production stability over years $t-2$ to t, whereas the baseline regressors are measured at year t. If the signs and broad qualitative patterns remain similar under this aligned specification, the results suggest that the baseline findings are not driven solely by end-of-window timing differences.

Table 11 provides further evidence on the robustness of the baseline results from the perspective of window-aligned specifications. Under both the temperature-shock and precipitation-shock window-aligned FE models, the main qualitative patterns remain broadly consistent: climate shock variables continue to show negative effects, farmland infrastructure retains a positive role, and most key interaction terms preserve the same general direction as in the baseline model. At the same time, the magnitude and statistical significance of some coefficients vary across the aligned specifications. This suggests that the baseline findings are not driven solely by timing mismatch between the dependent variable and the regressors, although the strength of some estimated effects remains sensitive to the exact alignment strategy. Overall, Table 11 indicates that the core empirical patterns remain broadly stable under the window-aligned fixed-effects framework, thereby lending additional support to the baseline conclusions.

Table 11. Window-aligned fixed-effects specifications.

Variables	Temperature-aligned FE	Precipitation-aligned FE
Temperature shock (3-period average)	-0.0107*** (0.0038)	-0.0306** (0.0131)
Precipitation shock (3-period average)	-0.0011 (0.0009)	-0.0017*** (0.0004)
Agricultural insurance (3-period average)	0.0122* (0.0069)	0.0078 (0.0050)
Farmland infrastructure (3-period average)	0.1610* (0.0823)	0.1580** (0.0681)
Insurance × Infrastructure	-0.0130** (0.0061)	-0.0197** (0.0094)
shock × Insurance	0.0019*** (0.0007)	-0.0061** (0.0025)
shock × Infrastructure	0.0172** (0.0080)	-0.0727** (0.0324)
shock × Insurance × Infrastructure	-0.0035** (0.0013)	-0.0145** (0.0055)
Agricultural mechanization	-0.0001 (0.0089)	-0.0002 (0.0088)
Cultivated land area	0.0122 (0.0141)	0.0183 (0.0156)
Labor input	-0.0097 (0.0092)	-0.0055 (0.0098)
Fertilizer use intensity	0.0320** (0.0151)	0.0348** (0.0139)
Urbanization	-0.0494 (0.0505)	-0.0324 (0.0577)
Planting structure	-0.0337 (0.0409)	-0.0313 (0.0455)
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Note: () reports standard errors. *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

5. Policy Recommendation

The empirical results of this paper show that agricultural insurance and farmland infrastructure do not exhibit a fixed synergistic relationship under all climate scenarios; their effects adjust with changes in the type and intensity of climate shocks. Overall, farmland infrastructure demonstrates a more stable and direct positive effect in enhancing grain production resilience; the direct effect of agricultural insurance is relatively weaker, but it can play a supplementary role under specific shock conditions. Especially under temperature shock scenarios, the supporting role of infrastructure is more prominent, while under strong precipitation shock scenarios, agricultural insurance and farmland infrastructure are more likely to show a complementary relationship. Based on this, this paper proposes the following policy implications:

First, greater emphasis should be placed on the fundamental role of farmland infrastructure in enhancing grain production resilience. Empirical results show that farmland infrastructure exhibits a relatively stable positive impact under different model settings, indicating that improving irrigation, drainage, and farmland engineering conditions can continuously enhance the ability of agricultural production systems to resist and absorb climate shocks. Compared with agricultural insurance, infrastructure acts more directly on the production process itself, thus having a more robust supporting significance in enhancing grain production resilience. Policy-wise, efforts should continue to promote the construction of high-standard farmland, improve water-saving irrigation systems, and upgrade irrigation and drainage facilities, with particular attention to infrastructure shortcomings in areas with high climate risk exposure.

Second, under temperature shock scenarios, farmland infrastructure should be considered a more critical adaptive tool. The results of this paper show that in temperature shock scenarios, the direct effect of agricultural insurance is generally weak, while farmland infrastructure maintains a positive effect under different conditions, with a more pronounced effect under high temperature shock conditions. Furthermore, agricultural insurance and farmland infrastructure are generally more of a substitute relationship, although this substitution weakens under higher temperature shock conditions, it does not significantly transform into a complementary relationship. This means that against the backdrop of continued warming or increased risks of extreme high temperatures, relying solely on insurance tools is insufficient to fully support the resilience of grain production; priority should be given to strengthening long-term infrastructure construction such as irrigation guarantees, field water conservancy, and farmland engineering conditions.

Third, under conditions of strong precipitation shocks, greater emphasis should be placed on the synergistic allocation of agricultural insurance and farmland infrastructure. This paper finds that under low precipitation impact conditions, agricultural insurance and farmland infrastructure do not exhibit a stable synergistic effect and even tend to substitute for each other. However, as precipitation impact intensifies, agricultural insurance, farmland infrastructure, and their interaction effects all improve, indicating that under scenarios of heavy precipitation, waterlogging, or increased drainage pressure, the two are more likely to form a complementary relationship. This result implies that in preventing floods and abnormal precipitation risks, relying solely on infrastructure is insufficient to continuously offset all losses, and the auxiliary role of risk-sharing tools such as insurance becomes more important. Therefore, in areas with high precipitation risk, the coordinated design of infrastructure investment and agricultural insurance coverage should be promoted to improve the overall efficiency of risk response.

Fourth, grain production support policies should shift from a uniform allocation to a dynamic adjustment mechanism that emphasizes risk classification and state dependence. This paper’s results indicate that the effectiveness of different policy tools is not constant but adjusts with changes in the type and intensity of climate shocks. Therefore, policy design should not be based on the assumption that a single tool is universally effective or that the same policy mix applies to all regions. Instead, it should be more targeted based on risk characteristics, regional differences, and shock states. For regions with significant high-temperature risks, greater emphasis should be placed on the long-term role of farmland infrastructure. For regions with large precipitation fluctuations and high flood risks, coordination between infrastructure construction and insurance coverage should be strengthened. Overall, enhancing grain production resilience cannot rely on a single policy tool but requires a more refined, differentiated, and dynamic policy mix system.

Future research can be further expanded in the following aspects. First, by incorporating micro-level data at the county or farmer level, the heterogeneity of policy effects under different operating scales, resource endowments, and risk exposure conditions can be identified more deeply. Second, in addition to temperature and precipitation shocks, extreme climate events such as droughts, floods, and heat waves can be included to more accurately reveal the impact mechanisms of different climate risks on grain production resilience. Third, future research can incorporate more adaptive tools, such as agricultural technology, credit support, and disaster early warning, into a unified framework to systematically examine the synergistic relationships among various policy tools. Finally, further attention can be paid to the long-term dynamic evolution of grain production resilience against the backdrop of continuously escalating climate risks, and whether policy effects will adjust with changes in the institutional environment and climate pressures.

6. Conclusions

This paper integrates agricultural insurance, farmland infrastructure, and climate shocks into a unified analytical framework to examine how different policy tools perform under varying climate scenarios from the perspective of grain production resilience. The results show that climate shocks significantly weaken grain production resilience, and that policy effects display clear nonlinear and state-dependent features. Overall, farmland infrastructure has a more stable and direct role in enhancing grain production resilience, whereas the direct effect of agricultural insurance is relatively limited, although it provides important supplementary support under specific shock conditions. In particular, under temperature shocks, the role of farmland infrastructure becomes more prominent, and the relationship between agricultural insurance and farmland infrastructure tends to be more substitutive. Under heavy precipitation shocks, by contrast, the two are more likely to become complementary. These findings suggest that improving grain production resilience cannot rely on any single policy instrument, but instead requires a more refined, differentiated, and dynamic policy mix tailored to different types of climate risks and levels of shock intensity.

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References

1. World Meteorological Organization. State of the Global Climate 2024, 19 March 2025. Available online: https://library.wmo.int/idurl/4/69455
2. Lobell, D.B.; Schlenker, W.; Costa-Roberts, J. Climate trends and global crop production since 1980. Science 2011, 333, 616–620. https://doi.org/10.1126/science.1204531
3. Ray, D.K.; Gerber, J.S.; MacDonald, G.K.; West, P.C. Climate variation explains a third of global crop yield variability. Nat. Commun. 2015, 6, 5989. https://doi.org/10.1038/ncomms6989
4. Lesk, C.; Rowhani, P.; Ramankutty, N. Influence of extreme weather disasters on global crop production. Nature 2016, 529, 84–87. https://doi.org/10.1038/nature16467
5. Zhao, C.; Liu, B.; Piao, S.; Wang, X.; Lobell, D.B.; Huang, Y.; et al. Temperature increase reduces global yields of major crops in four independent estimates. Proc. Natl. Acad. Sci. USA 2017, 114, 9326–9331. https://doi.org/10.1073/pnas.1701762114
6. Burke, M.; Emerick, K. Adaptation to climate change: Evidence from US agriculture. Am. Econ. J. Econ. Policy 2016, 8, 106–140. https://doi.org/10.1257/pol.20130025
7. Ortiz-Bobea, A.; Ault, T.R.; Carrillo, C.M.; Chambers, R.G.; Lobell, D.B. Anthropogenic climate change has slowed global agricultural productivity growth. Nat. Clim. Change 2021, 11, 306–312. https://doi.org/10.1038/s41558-021-01000-1
8. National Bureau of Statistics of China. Announcement on 2024 Grain Production Data, 13 December 2024. Available online: https://www.stats.gov.cn/sj/zxfb/202412/t20241213_1957744.html

9. National Bureau of Statistics of China. Bulletin on the National Grain Production in 2025, 15 December 2025. Available online: https://www.stats.gov.cn/english/PressRelease/202512/t20251215_1962079.html
10. National People's Congress of the People's Republic of China. Food Security Law of the People's Republic of China, 29 December 2023. Available online: https://www.npc.gov.cn/c2/c30834/202312/t20231229_433989.html
11. Darnhofer, I. Resilience and why it matters for farm management. Eur. Rev. Agric. Econ. 2014, 41, 461–484. https://doi.org/10.1093/erae/jbu012
12. Tendall, D.M.; Joerin, J.; Kopainsky, B.; Edwards, P.; Shreck, A.; Le, Q.B.; et al. Food system resilience: Defining the concept. Glob. Global Food Security. 2015, 6, 17–23. https://doi.org/10.1016/j.gfs.2015.08.001
13. Urruty, N.; Tailliez-Lefebvre, D.; Huyghe, C. Stability, robustness, vulnerability and resilience of agricultural systems. A review. Agron. Sustain. Dev. 2016, 36, 15. https://doi.org/10.1007/s13593-015-0347-5
14. Hennessy, D.A. The production effects of agricultural income support policies under uncertainty. Am. J. Agric. Econ.1998, 80, 46–57. https://doi.org/10.2307/3180267
15. Cole, S.; Giné, X.; Tobacman, J.; Topalova, P.; Townsend, R.; Vickery, J. Barriers to household risk management: Evidence from India. Am. Econ. J. Appl. Econ. 2013, 5, 104–135. https://doi.org/10.1257/app.5.1.104
16. Karlan, D.; Osei, R.; Osei-Akoto, I.; Udry, C. Agricultural decisions after relaxing credit and risk constraints. Q. J. Econ. 2014, 129, 597–652. https://doi.org/10.1093/qje/qju002
17. Siebert, S.; Burke, J.; Faures, J.M.; Frenken, K.; Hoogeveen, J.; Döll, P.; Portmann, F.T. Groundwater use for irrigation—A global inventory. Hydrol. Earth Syst. Sci. 2010, 14, 1863–1880. https://doi.org/10.5194/hess-14-1863-2010
18. Fuglie, K.O. Is agricultural productivity slowing? Global Food Security. 2018, 17, 73–83. https://doi.org/10.1016/j.gfs.2018.05.001
19. Dercon, S.; Hill, R.V.; Clarke, D.; Outes-Leon, I.; Taffesse, A.S. Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia. J. Dev. Econ. 2014, 106, 132–143. https://doi.org/10.1016/j.jdeveco.2013.09.006
20. Chambers, R.G.; Quiggin, J. Optimal producer behavior in the presence of area-yield crop insurance. Am. J. Agric. Econ. 2002, 84, 320–334. https://doi.org/10.1111/1467-8276.00300
21. Glauber, J.W. The growth of the federal crop insurance program, 1990–2011. Am. J. Agric. Econ. 2013, 95, 482–488. https://doi.org/10.1093/ajae/aas091
22. Schlenker, W.; Roberts, M.J. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proc. Natl. Acad. Sci. USA 2009, 106, 15594–15598. https://doi.org/10.1073/pnas.0906865106
23. Dell, M.; Jones, B.F.; Olken, B.A. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J. Macroecon. 2012, 4, 66–95. https://doi.org/10.1257/mac.4.3.66
24. Hsiang, S. Climate econometrics. Annu. Rev. Resour. Econ. 2016, 8, 43–75. https://doi.org/10.1146/annurev-resource-100815-095343
25. Auffhammer, M.; Hsiang, S.M.; Schlenker, W.; Sobel, A. Using weather data and climate model output in economic analyses of climate change. Rev. Environ. Econ. Policy 2013. https://doi.org/10.1093/reep/ret016
26. Cole, S.A.; Xiong, W. Agricultural insurance and economic development. Annu. Rev. Econ. 2017, 9, 235–262. https://doi.org/10.1146/annurev-economics-080315-015225
27. Janzen, S.A.; Carter, M.R. After the drought: The impact of microinsurance on consumption smoothing and asset protection. Am. J. Agric. Econ. 2019, 101, 651–671. https://doi.org/10.1093/ajae/aay061
28. Stoeffler, Q.; Carter, M.; Guirkinger, C.; Gelade, W. The spillover impact of index insurance on agricultural investment by cotton farmers in Burkina Faso. World Bank Econ. Rev. 2022, 36, 114–140. https://doi.org/10.1093/wber/lhab011
29. Jensen, N.D.; Barrett, C.B.; Mude, A.G. Index insurance quality and basis risk: Evidence from northern Kenya. Am. J. Agric. Econ. 2016, 98, 1450–1469. https://doi.org/10.1093/ajae/aaw046
30. King, M.; Singh, A.P. Understanding farmers' valuation of agricultural insurance: Evidence from Vietnam. Food Policy2020, 94, 101861. https://doi.org/10.1016/j.foodpol.2020.101861

31. You, L.; Ringler, C.; Wood-Sichra, U.; Robertson, R.; Wood, S.; Zhu, T.; et al. What is the irrigation potential for Africa? A combined biophysical and socioeconomic approach. Food Policy 2011, 36, 770–782. https://doi.org/10.1016/j.foodpol.2011.09.001
32. Zhang, X.; Cai, X. Climate change impacts on global agricultural water deficit. Geophys. Res. Lett. 2013, 40, 1111–1117. https://doi.org/10.1002/grl.50279
33. Ward, F.A.; Pulido-Velazquez, M. Water conservation in irrigation can increase water use. Proc. Natl. Acad. Sci. USA2008, 105, 18215–18220. https://doi.org/10.1073/pnas.0805554105
34. Skees, J.R.; Hartell, J.; Murphy, A.G. Using index-based risk transfer products to facilitate micro lending in Peru and Vietnam. Am. J. Agric. Econ. 2007, 89, 1255–1261. https://doi.org/10.1111/j.1467-8276.2007.01093.x
35. Carter, M.; De Janvry, A.; Sadoulet, E.; Sarris, A. Index insurance for developing country agriculture: A reassessment. Annu. Rev. Resour. Econ. 2017, 9, 421–438. https://doi.org/10.1146/annurev-resource-100516-053352
36. Emerick, K.; De Janvry, A.; Sadoulet, E.; Dar, M.H. Technological innovations, downside risk, and the modernization of agriculture. Am. Econ. Rev. 2016, 106, 1537–1561. https://doi.org/10.1257/aer.20150474
37. Orden, D.; Blandford, D.; Josling, T., Eds. WTO Disciplines on Agricultural Support: Seeking a Fair Basis for Trade; Cambridge University Press: Cambridge, UK, 2011; pp. 45–68.
38. Barrios, S.; Bertinelli, L.; Strobl, E. Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. Rev. Econ. Stat. 2010, 92, 350–366. https://doi.org/10.1162/rest.2010.11212
39. Hornbeck, R.; Keskin, P. The historically evolving impact of the Ogallala Aquifer: Agricultural adaptation to groundwater and drought. Am. Econ. J. Appl. Econ. 2014, 6, 190–219. https://doi.org/10.1257/app.6.1.190
40. Tack, J.; Barkley, A.; Hendricks, N. Irrigation offsets wheat yield reductions from warming temperatures. Environ. Res. Lett. 2017, 12, 114027. https://doi.org/10.1088/1748-9326/aa8d27
41. Climate Data Store. *ERA5 hourly data on single levels from 1940 to present*; 2024. https://doi.org/10.24381/cds.adbb2d47
42. Runfola, D.; Community Contributors. geoBoundaries: A global database of political administrative boundaries. PLoS ONE 2020, 15(4), e0231866. https://doi.org/10.1371/journal.pone.0231866
43. Knapp, S.; van der Heijden, M.G. A global meta-analysis of yield stability in organic and conservation agriculture. Nat. Commun. 2018, 9, 3632. https://doi.org/10.1038/s41467-018-05956-1
44. Döring, T.F.; Reckling, M. Detecting global trends of cereal yield stability by adjusting the coefficient of variation. Eur. J. Agron. 2018, 99, 30–36. https://doi.org/10.1016/j.eja.2018.06.007
45. Zampieri, M.; Weissteiner, C.J.; Grizzetti, B.; Toreti, A.; van den Berg, M.; Dentener, F. Estimating resilience of crop production systems: From theory to practice. Sci. Total Environ. 2020, 735, 139378. https://doi.org/10.1016/j.scitotenv.2020.139378
46. Jägermeyr, J.; Frieler, K. Spatial variations in crop growing seasons pivotal to reproduce global fluctuations in maize and wheat yields. Sci. Adv. 2018, 4, eaat4517. https://doi.org/10.1126/sciadv.aat4517
47. Nes, K.; Schaefer, K.A.; Gammans, M.; Scheitrum, D.P. Extreme weather events, climate expectations, and agricultural export dynamics. Am. J. Agric. Econ. 2025, 107, 826–845. https://doi.org/10.1111/ajae.12505