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# Geographical Indications and Agricultural Economic Resilience: Evidence from China

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## Abstract

This study examines the impact of agricultural geographical indications on agricultural economic resilience and its underlying mechanisms, using provincial-level panel data from China covering 2008 to 2020. Employing fixed-effects panel models, spatial Durbin models, and mediation analysis, we find that agricultural geographical indications significantly enhance agricultural economic resilience in the originating region. However, a siphoning effect is observed: geographical indications exert a negative spatial spillover on agricultural economic resilience in neighboring provinces. Mechanism analysis reveals that geographical indications strengthen resilience through three channels: brand spillover, industrial agglomeration , and structural upgrading. This study contributes to the literature on the public value of agricultural geographical indications and offers policy insights for China and comparable economies seeking to reinforce geographical indication construction and bolster agricultural economic resilience.

**Keywords:** agricultural economic resilience; geographical indications; brand spillover; industrial agglomeration; structural upgrading

## 1. Introduction

Amid accelerating global transformations and mounting economic uncertainties, the stable growth of agriculture—as a foundational sector of the national economy—is directly linked to high-quality economic development. Agriculture worldwide faces increasingly severe challenges, including climate change, natural disasters, and market volatility, which not only affect farmers' livelihoods but also place greater demands on the stability and sustainability of the entire agri-food system (Guedegbe et al., 2023). China's annual Central Document No. 1 has repeatedly emphasized the need to proactively address internal and external risks to agricultural development, ensure stable production and supply of grain and key agricultural products, and promote sound economic and social development (Yang et al., 2022). Consequently, reducing the impact of external shocks on the agricultural economy and strengthening its resistance and recovery capacity—i.e., enhancing agricultural economic resilience—is critical to building a strong agricultural nation and safeguarding global food security.

Existing studies have examined agricultural economic resilience from two perspectives: measurement methods and influencing factors. Regarding measurement, most scholars construct indicator systems based on the Pressure-State-Response (PSR) framework, capturing the shocks faced by agricultural development, the state of the agricultural economy, and corresponding responses (Martin, 2012; Tang and Chen, 2023). Others have developed comprehensive evaluation index systems from production, ecological, and economic dimensions (Jiang, 2022), though no consensus has emerged on the optimal measurement approach. As for influencing factors, government interventions such as EU Common Agricultural Policy direct payments (Žičkienė et al., 2022), fiscal subsidy policies (Quandt, 2023), and agricultural insurance (Zhang and Jiao,

2022) can effectively compensate for agriculture's inherent vulnerability and thereby enhance resilience. In addition, regional digital economy development (Zhao and Xu, 2023), financial development (Liu et al., 2021), agricultural infrastructure (Tang and Chen, 2023), and industrial integration (Hao and Tan, 2023) are also identified as important determinants of agricultural economic resilience.

Geographical indications serve as a powerful instrument for quality assurance and value upgrading of regional agricultural products. Agricultural geographical indications designate unique products originating from a specific region, whose quality and characteristics are primarily attributable to the natural ecological environment and historical-cultural factors, and which bear the region's name (Aprile et al., 2012). GI labeling enhances the credibility and perceived quality of agricultural products, raising their added value and market competitiveness. Prior research has demonstrated that geographical indications can improve product quality and safety (Moschini et al., 2008), increase farmers' income and living standards (Suh and Macpherson, 2010), reduce rural poverty (Durand and Fournier, 2017), and promote socioeconomic and environmental sustainability (Rabadán et al., 2021).

Despite the growing body of research on both agricultural geographical indications and agricultural economic resilience, few studies have systematically investigated whether and how geographical indications affect agricultural economic resilience. Can agricultural geographical indications enhance resilience? What is the magnitude and direction of their impact? What are the underlying transmission mechanisms? And do spatial spillover effects exist? Addressing these questions provides theoretical support for governments to continue promoting GI construction and carries practical significance for advancing the stable and sustainable development of Chinese agriculture.

Against this backdrop, this study uses panel data from 31 Chinese provinces over 2008–2020 and employs baseline regression and spatial econometric models to test the impact of agricultural geographical indications on agricultural economic resilience. The marginal contributions are threefold. First, by examining the effect of agricultural geographical indications with agricultural economic resilience as the outcome variable, this study enriches the GI literature and offers a new perspective for enhancing agricultural economic resilience. Second, we construct an evaluation index system of agricultural economic resilience from three dimensions—risk resistance, adjustment and recovery, and growth and development—using the entropy method, providing a useful supplement to existing measurement approaches. Third, we elucidate the transmission mechanisms through which geographical indications affect resilience via brand spillover, industrial agglomeration, and structural upgrading effects, thereby identifying additional pathways for leveraging agricultural geographical indications to strengthen agricultural economic resilience.

## 2. Theoretical analysis and research hypotheses

### 2.1 Geographical indications and agricultural economic resilience

Agriculture is inherently dependent on natural resources—a characteristic often described as "living off the land." geographical indications, possessing attributes of public goods, have become a critical resource for the competitive advantage of regional agricultural products and can effectively reduce agricultural vulnerability (Kalogiannidis et al., 2023). Agricultural economic resilience is a multifaceted concept reflecting the capacity of the agricultural economy to withstand external shocks, respond promptly, and effectively adjust to achieve recovery (Berry et al., 2022). Agricultural geographical indications are a key driver of farmers' income growth, product quality improvement, and production efficiency gains (Sepúlveda et al., 2010; Lee et al., 2020). Through

GI branding, regional agricultural products establish strong market reputations (Menapace and Moschini, 2010), enhancing their recognition and competitiveness and laying a foundation for improved resilience.

Three specific channels link geographical indications to resilience. First, GI construction requires farmers to adopt ecologically sustainable production methods and imposes strict limits on chemical fertilizer and pesticide use, thereby strengthening agro-ecological protection (Gai and Yang, 2023). A sound agro-ecological environment, in the long run, enhances the resistance capacity of agricultural operations (Bowen and Zapata, 2009). Second, geographical indications convey information about the origin, quality, and flavor of products shaped by unique local natural and climatic conditions, helping agricultural products gain differentiated competitive advantages and expand market potential and economic returns (Teuber, 2011). Cultivating distinctive product brands facilitates the integration of production factors, the formation of agricultural clusters, and further improvements in operational resilience. Third, geographical indications effectively transform the low-specialization and low-refinement characteristics of traditional agriculture by leveraging local resource endowments to create unique brands, promoting specialized division of labor and refined production, advancing regional agricultural modernization, and enhancing the growth capacity of agricultural operations (Qin et al., 2021).

**Hypothesis 1: Agricultural geographical indications significantly enhance agricultural economic resilience in the originating region.**

## 2.2 Mechanisms through which geographical indications influence agricultural economic resilience

Drawing on resource-based theory and externality theory, geographical indications endow products with unique attributes that serve not only as a source of market competitiveness for

114 regional agriculture but also as a strategic resource for enhancing agricultural economic resilience.
115 Specifically, geographical indications strengthen resilience through three mechanisms: brand
116 premium, industrial agglomeration, and structural upgrading.

117 First, agricultural geographical indications generate a brand premium effect, raising farmers'
118 income and promoting regional agricultural development, thereby enhancing resilience. From an
119 information asymmetry perspective, agricultural products are non-standardized, placing
120 consumers at an information disadvantage during purchase. geographical indications perform a
121 signaling function that improves consumer recognition and loyalty (Sorgho and Larue, 2014).
122 Moreover, geographical indications enable less-developed regions to capitalize on natural
123 resources, develop rural agritourism, promote return migration and local employment, and
124 invigorate regional agricultural development (Crescenzi et al., 2021). Thus, by leveraging product
125 uniqueness to gain competitive advantages, build regional specialty brands, and increase premium
126 capacity, geographical indications raise farmers' income and empower agricultural economic
127 resilience.

128 Second, agricultural geographical indications exert an industrial agglomeration effect,
129 realizing economies of scale and thereby enhancing resilience. Rooted in unique natural resources,
130 geographical indications attract the concentration of various production factors within the region
131 (Ren and Lei, 2022), creating a virtuous cycle for agricultural economic development and a steady
132 flow of resources for resilience building (Vecchio et al., 2020). geographical indications also draw
133 investment and R&D resources into the agricultural sector, and by strengthening cooperation
134 among agricultural entities, they accelerate the diffusion and adoption of new technologies
135 (Meuwissen et al., 2019). In the face of natural disasters, market fluctuations, and economic
136 uncertainty, the agglomeration and technology-diffusion effects of GI products elevate the

technological level and competitiveness of agriculture, further enhancing resilience (Jung et al., 2021).

Third, agricultural geographical indications produce a structural upgrading effect, optimizing the agricultural industry chain and thereby enhancing resilience. On the one hand, geographical indications possess high economic and social value due to their unique geographical characteristics and quality assurance, generating not only direct income but also driving tourism, services, and related industries, and promoting diversified regional agricultural development (Qin et al., 2021). On the other hand, GI adoption promotes the integration and coordinated development of the agricultural value chain. Through GI establishment, the production, processing, and marketing of agricultural products are effectively regulated and coordinated, improving the efficiency and competitiveness of the entire chain (Wang et al., 2021). Furthermore, the optimization of diversified industrial structures and chains reduces farmers' business risks and strengthens the risk resistance and recovery capacity of the agricultural economy (Lin, 2011; Zampieri et al., 2020; Liang and Liu, 2023).

**Hypothesis 2: Agricultural geographical indications enhance regional agricultural economic resilience through brand premium, industrial agglomeration, and structural upgrading effects.**

### 2.3 Spatial spillover effects of geographical indications on agricultural economic resilience

Based on regional characteristic brands, agricultural geographical indications may also generate spatial spillover effects beyond their originating region. On the positive side, a "radiation effect" can emerge: the GI development model in one region provides a reference for neighboring regions to cultivate their own characteristic geographical indications. Neighboring provinces can design GI development strategies aligned with their own resource endowments and advantages,

thereby enhancing their own agricultural economic resilience (Zhao and Xu, 2023). Additionally, GI construction in one region facilitates the flow of advanced agricultural technologies, talent, and other factors, contributing to market expansion and factor allocation in neighboring regions and providing conditions for resilience improvement there (Tang and Chen, 2023).

Conversely, a "siphoning effect" may also arise. Geographic proximity often implies similarity in agricultural products, which can reduce market demand for neighboring regions' products and disadvantage their agricultural development (Ma and Yan, 2019). For instance, Yangcheng Lake hairy crabs enjoy a strong brand advantage and greater consumer recognition, while crabs from neighboring regions—despite similar quality—face substantially lower prices and weaker sales. Moreover, the industrial agglomeration effect of local geographical indications not only attracts labor from neighboring regions but may also capture a disproportionate share of government policy support and financial resources, leaving neighboring regions deficient in human capital and market vitality. Consequently, the spatial spillover of geographical indications may be detrimental to agricultural economic resilience in neighboring regions.

**Hypothesis 3a: Agricultural geographical indications exert a positive "radiation effect" on agricultural economic resilience in neighboring regions.**

**Hypothesis 3b: Agricultural geographical indications exert a negative "siphoning effect" on agricultural economic resilience in neighboring regions.**

# 3. Research design

## 3.1 Model specification

To verify the impact of agricultural geographical indications on agricultural economic resilience, we construct the following baseline econometric model, drawing on Liao (2021):

$$AER_{it} = \beta_0 + \beta_1 * GI_{it} + \beta_2 * Controls_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (1)$$

where *i* and *t* denote provinces and years, respectively. $GI_{it}$ represents the stock of agricultural geographical indications in region i in year t. $AER_{it}$ denotes agricultural economic resilience, further decomposed into risk resistance (R1), adjustment and recovery (R2), and growth and development (R3). Controls represents the set of control variables; $\gamma_i$ captures province fixed effects, $\mu_t$ captures time fixed effects, and $\varepsilon_{it}$ is the error term.

To test spatial spillover effects, we employ the Spatial Durbin Model (SDM), which can more comprehensively estimate spatial spillovers in panel data. The model is specified as follows:

$$AER_{it} = \alpha_0 + \alpha_1 * GI_{it} + \alpha_2 * Controls + \gamma_i + \mu_t + \varphi W * Rec_{it} + \rho_1 W * Brand_{it} + \Sigma\rho_2 W * Controls_{it} + \varepsilon_{it} \quad (2)$$

where *W* denotes the spatial weight matrix and are the estimated coefficients of the spatial lag terms of the explanatory and control variables.

To further investigate the transmission mechanisms, we construct the following mediation effect model:

$$M_{it} = \theta_0 + \theta_1 * GI_{it} + \vartheta_2 * Controls_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (1)$$

where $M_{it}$ denotes the mediating variable.

## 3.2 Variable definitions

**Dependent variable — Agricultural Economic Resilience (AER)**

Research on agricultural economic resilience remains at a relatively early stage, with no consensus on its conceptual definition. Drawing on Meuwissen et al. (2019), this study defines agricultural economic resilience as the capacity of an agricultural economy to respond effectively and promptly to unexpected shocks through its resource reserves and internal capabilities, thereby

achieving rapid recovery and growth. The Pressure-State-Response (PSR) model, grounded in dynamic systems theory, has been widely applied in assessment studies. Based on the PSR framework and the foregoing conceptual analysis, we construct an evaluation index system from three dimensions: risk resistance, adjustment and recovery, and growth and development (Štreimikienė et al., 2022; Meuwissen et al., 2019). Indicator weights are determined using the entropy method. The resulting index system is presented in Table 1.

**Table 1 Evaluation index system for agricultural economic resilience**

| Level 1 indicators | Secondary indicators | Tertiary indicators | Description of indicators | characteristic |
|---|---|---|---|---|
| Risk resistance | Gross agricultural output | Agriculture, forestry and fisheries GDP (billions of dollars) | Response to the effects of agricultural production | + |
| | Degree of disaster | Area affected by crops (thousands of hectares) | Responding to disaster losses | - |
| | Farmers' income | Disposable income of rural residents (yuan) | Responding to farmers' income levels | + |
| | Irrigation | Effective irrigated area (thousands of hectares) | Reactive agricultural water facilities | + |
| Adjustment of resilience | Financial support for agriculture | Amount of expenditure on farmland and water affairs (ten thousand yuan) | Responding to government support for agricultural development | + |
| | agricultural insurance | Amount of agricultural insurance coverage (millions of dollars) | Increasing agricultural income security | + |
| | Agricultural loans | Amount of agriculture-related loans by financial institutions (billions of yuan) | Financial security for agricultural recovery | + |
| | mechanization level | Total power of agricultural machinery (million kWh) | Contribute to the recovery of agricultural production | + |

| | | | | |
|---|---|---|---|---|
| | educational level | Average years of schooling of rural residents (years) | Human support for rapid agricultural recovery | + |
| | Transportation infrastructure | Miles of rural roads (kilometers) | Promoting agricultural development and market expansion | + |
| Growing the Power of Change | human capital | Number of students enrolled in undergraduate programs (10,000) | Increasing opportunities for future development of agriculture | + |
| | Financial expenditure on science and technology | Local Government Expenditures on Agricultural Science and Technology (million yuan) | Contribute to the improvement of agricultural science and technology | + |
| | electricity consumption | Electricity consumption in agricultural production (million kWh) | Responding to the development potential of agricultural production | + |
| | informatization level | Number of Internet broadband access subscribers (10,000) | Responding to mastery of agricultural information | + |

*Note: Compiled by the authors.*

**Explanatory variable — Geographical Indication (GI)**

Following Liu et al. (2016) and considering data authority and availability, we measure GI using the regional stock of agricultural geographical indication products. Data on GI stock are compiled from the Trademark Law of the People's Republic of China, the Provisions on the Protection of Geographical Indication Products, and the Measures for the Administration of Geographical Indications of Agricultural Products. Records are manually screened, cleaned, and aggregated to obtain the annual stock of agricultural geographical indications for each province from 2008 to 2020. To mitigate potential estimation bias, the GI stock is log-transformed.

**Control variables**

To avoid omitted-variable bias, we select the following control variables based on existing literature: (1) economic development level (GGDP), measured as the logarithm of regional per capita GDP; (2) industrial structure (Structure), measured as the share of secondary and tertiary industry value-added in GDP; (3) trade openness (Open), measured as the ratio of total imports and exports to GDP; (4) urbanization level (Urban), measured as the share of urban population in total population; (5) soil and water conservation (Water), measured as the ratio of soil erosion control area to total sown area; and (6) transportation infrastructure (Infra), measured as the density of railways, highways, and inland waterways relative to provincial land area.

### 3.3 Sample selection and data sources

Given data availability for the agricultural economic resilience indicators, the initial sample comprises 31 Chinese provinces (autonomous regions and municipalities). After excluding observations with missing values for key variables, the final regression sample includes 29 provinces over 2008–2020. GI brand data are sourced from the China Trademark Network (State Intellectual Property Office), the Geographical Indications Network, and the Agricultural Products Geographical Indications Information Query System. Other data are obtained from the China Statistical Yearbook, the National Bureau of Statistics, the China Rural Statistical Yearbook, the CSMAR database, and the China Banking and Insurance Regulatory Commission. Missing values are filled using linear interpolation.

### 3.4 Descriptive statistics

Table 2 reports the descriptive statistics of all variables. Comparison with prior studies indicates that the means and standard deviations are consistent with existing findings. AER has a mean of 0.210, with a minimum of 0.028 and a maximum of 0.639, suggesting that China's

agricultural economic resilience remains relatively low with substantial regional disparities. GI (log-transformed stock) has a mean of 1.706, ranging from 0 to 4.159. The control variables also exhibit considerable cross-sectional variation, indicating good sample differentiation.

**Table 2 Descriptive statistics**

| variant | sample | average | standard deviation | upper quartile | minimum | maximum |
|---|---|---|---|---|---|---|
| AER | 374 | 0.21 | 0.128 | 0.179 | 0.028 | 0.639 |
| R1 | 374 | 0.062 | 0.03 | 0.055 | 0.012 | 0.144 |
| R2 | 374 | 0.072 | 0.052 | 0.062 | 0.006 | 0.240 |
| R3 | 374 | 0.06 | 0.054 | 0.044 | 0 | 0.291 |
| GI | 374 | 1.706 | 1.049 | 1.792 | 0 | 4.159 |
| GGDP | 374 | 10.63 | 0.536 | 10.63 | 9.180 | 12.01 |
| Structure | 374 | 0.902 | 0.051 | 0.902 | 0.713 | 0.997 |
| Open | 374 | 0.02 | 0.029 | 0.009 | 0 | 0.150 |
| Urban | 374 | 0.445 | 0.088 | 0.454 | 0.219 | 0.881 |
| Water | 374 | 1.045 | 1.112 | 0.737 | 0 | 10.18 |
| Gap | 374 | 2.683 | 0.426 | 2.605 | 1.845 | 3.952 |

# 4. Empirical results

## 4.1 Baseline regression results

Table 3 presents the baseline regression results, with province and time fixed effects controlled in all specifications. Columns (1)–(4) include only the two-way fixed effects and show that agricultural geographical indications significantly improve risk resistance, adjustment and recovery, growth and development, and overall agricultural economic resilience. Columns (5)–(8) further incorporate the control variables. The coefficient of GI on overall AER is 0.014, significant at the 1% level, indicating that a one-unit increase in the GI stock is associated with a 1.4% increase

in agricultural economic resilience. The results confirm that agricultural geographical indications possess clear value attributes and significantly enhance regional agricultural economic resilience, supporting Hypothesis 1.

**Table 3 Baseline regression results**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | AER | R1 | R2 | R3 | AER |
| GI | 0.046*** | 0.012*** | 0.020*** | 0.009** | 0.044*** | 0.009*** | 0.016*** | 0.014*** |
| | (3.94) | (3.80) | (4.36) | (2.31) | (4.18) | (3.45) | (3.65) | (3.86) |
| GGDP | | | | | 0.096 | 0.004 | 0.017 | 0.062* |
| | | | | | (1.28) | (0.23) | (0.64) | (1.77) |
| Structure | | | | | 0.241 | 0.041 | 0.119 | 0.105 |
| | | | | | (0.48) | (0.27) | (0.65) | (0.74) |
| Open | | | | | -0.201 | -0.143 | -0.414** | 0.544 |
| | | | | | (-0.29) | (-0.89) | (-2.05) | (1.53) |
| Urban | | | | | -0.392** | -0.097*** | -0.053 | -0.204*** |
| | | | | | (-2.66) | (-3.07) | (-1.11) | (-3.29) |
| Water | | | | | -0.042** | -0.009* | -0.016** | -0.013* |
| | | | | | (-2.46) | (-1.91) | (-2.53) | (-1.98) |
| Gap | | | | | -0.041 | -0.018 | -0.016 | -0.002 |
| | | | | | (-0.80) | (-1.37) | (-0.96) | (-0.08) |
| Fixed time and province | YES | YES | YES | YES | YES | YES | YES | YES |
| _cons | 0.131*** | 0.042*** | 0.039*** | 0.044*** | -0.770 | 0.068 | -0.145 | -0.616* |
| | (5.58) | (7.31) | (4.54) | (4.10) | (-1.03) | (0.38) | (-0.56) | (-1.76) |
| *N* | 374 | 374 | 374 | 374 | 374 | 374 | 374 | 374 |
| *Adj_R²* | 0.221 | 0.142 | 0.390 | 0.042 | 0.449 | 0.353 | 0.513 | 0.463 |

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

## 4.2 Robustness tests

Replacement of estimation method. Since the entropy method yields AER values bounded between 0 and 1, the dependent variable satisfies the conditions for a censored regression model. We therefore re-estimate Equation (1) using a panel Tobit model. As shown in column (1) of Table 4, the GI coefficient is 0.036 and significant at the 1% level, confirming that the positive relationship between geographical indications and agricultural economic resilience is robust to alternative estimation methods.

Exclusion of municipalities. Municipalities differ substantially from other provinces in taxation, fiscal support, and transportation infrastructure—factors that may influence how geographical indications affect agricultural economic resilience. To rule out this confounding effect, we exclude the four municipalities from the sample and re-estimate the model. Column (2) of Table 4 shows that the GI coefficient remains 0.029 and significant at the 1% level, again verifying Hypothesis 1.

Instrumental variable approach. Although the two-way fixed-effects model mitigates some estimation bias, endogeneity concerns may persist. Following Zhang and Pi (2022), we use topographic relief (terrain undulation) as an instrumental variable for GI. Topographic relief affects the growing environment and quality characteristics (flavor, aroma, nutrient content) of agricultural products, satisfying the relevance condition. Meanwhile, topographic relief is not directly related to the defense, recovery, and growth capacity of the agricultural economic system, satisfying the exclusion restriction. Columns (3)–(4) of Table 4 report the IV results. Topographic relief is significantly negatively correlated with GI, and the IV-estimated GI coefficient remains significantly positive, corroborating the main findings.

**Table 4 Robustness test results**

| | Replacement of the estimation model | Cities excluded from the sample | 2SLS | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| GI | 0.036*** | 0.029*** | | 0.191*** |
| | (6.58) | (3.51) | | (2.62) |
| IV | | | -0.135** | |
| | | | (-2.23) | |
| control variable | YES | YES | YES | YES |
| Fixed time and province | YES | YES | YES | YES |
| _cons | -0.837*** | -1.308*** | -5.72* | -0.898 |
| | (-3.77) | (-4.52) | (-1.71) | (-1.20) |
| *N* | 374 | 322 | 231 | 231 |
| *Adj_R²* | | 0.662 | 0.153 | 0.052 |

## 4.3 Spatial spillover effect analysis

### Spatial model selection

Spatial effect analysis requires balanced panel data. After excluding provinces with missing years, we use data from 28 provinces over 2008–2020. We conduct LM and LR tests to select the appropriate spatial econometric model (Table 5). Both the spatial error and spatial lag models yield p-values below 0.1, indicating significant LM statistics and the presence of both spatial error and spatial lag terms. The LR tests are all significant at the 1% level. We therefore adopt the spatial Durbin model (SDM) for the spatial effect analysis.

**Table 5 LM and LR test results**

| Test Methods | statistic | P-value |
|---|---|---|
| spatial error | | |
| Moran's I | 3.090 | 0.002 |
| Lagrange multiplier | 8.534 | 0.003 |
| Robust Lagrange multiplier | 3.370 | 0.066 |
| spatial lag | | |
| Lagrange multiplier | 7.415 | 0.006 |
| Robust Lagrange multiplier | 3.303 | 0.069 |
| LR test | | |
| LR-SDM-SAR | 31.83 | 0.000 |
| LR-SDM-SEM | 23.90 | 0.0012 |

## Spatial effect analysis

We construct a spatial weight matrix based on provincial contiguity and use the partial derivative method to decompose spatial effects into direct, indirect, and total effects (Table 6). The direct effect of GI on local agricultural economic resilience is 0.031, significant at the 1% level (column 1), indicating that a one-unit increase in GI stock raises local resilience by 0.031. Compared with the baseline coefficient of 0.014, the direct effect is larger by 0.017, suggesting that the resilience-enhancing effect of geographical indications would be underestimated if spatial spillovers are ignored.

The indirect effect of GI on neighboring regions' agricultural economic resilience is −0.014, significant at the 10% level (column 2), indicating that a one-unit increase in local GI stock reduces neighboring regions' resilience by 0.014. This finding confirms a siphoning effect: through industrial agglomeration, local geographical indications absorb more labor and capture larger

market shares, depriving neighboring regions of resources needed for agricultural development and thereby reducing their resilience. Hypothesis 3b is supported.

**Table 6 Spatial effects of agricultural geographical indications on agricultural economic resilience**

| | (1) direct effect | (2) indirect effect | (3) aggregate effect |
|---|---|---|---|
| GI | 0.031*** | -0.014* | 0.017* |
| | (5.15) | (-1.77) | (1.73) |
| GGDP | 0.081*** | 0.063 | 0.144** |
| | (2.71) | (1.17) | (2.43) |
| Structure | 0.550*** | 0.071 | 0.621* |
| | (3.41) | (0.22) | (1.78) |
| Open | -0.294 | 1.215* | 0.920 |
| | (-0.98) | (1.80) | (1.30) |
| Urban | -0.405*** | -0.353** | -0.758*** |
| | (-4.94) | (-2.18) | (-3.59) |
| Water | -0.048*** | -0.015 | -0.063*** |
| | (-7.75) | (-1.35) | (-4.49) |
| Gap | -0.042* | -0.000 | -0.042 |
| | (-1.92) | (-0.00) | (-0.91) |
| Fixed time & province | YES | YES | YES |
| rho | | | -0.199* |
| | | | (-1.80) |
| sigma2_e | | | 0.008*** |
| | | | (13.25) |
| Time/province fixed | YES | YES | YES |
| sample size | 364 | 364 | 364 |

# 5. Further analysis

## 5.1 Mechanism tests

The preceding results establish that geographical indications enhance agricultural economic resilience. We now examine the specific transmission mechanisms. As discussed, geographical indications may operate through brand premium, industrial agglomeration, and structural upgrading effects. The brand premium effect is proxied by the agricultural product price index (Price). Industrial agglomeration is captured by two measures: the degree of industrial agglomeration (Gather), measured as the ratio of forestry, animal husbandry, and fishery output to total agricultural output; and technological progress (Tech), measured as the ratio of total agricultural machinery power to agricultural employment. Structural upgrading is measured by industrial rationalization (TL) and industrial advancement (EI). Rationalization is measured using a modified Theil index, computed as the product of each sub-sector's output share and the corresponding employment share. Advancement is measured as the share of agricultural services output in total agricultural output.

Following Jiang (2022), we verify the transmission mechanisms by testing whether the core explanatory variable (GI) significantly affects each mediating variable, combined with theoretical deduction of the mediator's effect on the outcome. Table 7 reports the results. In column (1), the GI coefficient on Price is 1.359, significant at the 1% level, indicating that geographical indications significantly raise agricultural product prices—consistent with the brand spillover effect. In columns (2) and (3), the GI coefficients on Gather and Tech are 0.010 and 0.681, respectively, both significant at least at the 10% level, confirming that geographical indications promote industrial agglomeration and technological progress—the agglomeration effect. In columns (4) and (5), the GI coefficients on TL and EI are 0.023 and −0.017, respectively, both significant at least at the 10% level, indicating that geographical indications enhance both the rationalization

and advancement of the agricultural industrial structure—the structural upgrading effect. Collectively, these results verify Hypothesis 2.

**Table 7 Mechanism test regression results**

| | (1) Price | (2) Gather | (3) Tech | (4) TL | (5) EI |
|---|---|---|---|---|---|
| GI | 1.359** | 0.010*** | 0.681* | 0.023*** | -0.017* |
| | (2.42) | (4.32) | (1.83) | (3.85) | (-1.91) |
| control variable | YES | YES | YES | YES | YES |
| Fixed time & province | YES | YES | YES | YES | YES |
| _cons | 65.048*** | -0.010 | 5.445 | 0.548 | 0.552 |
| | (2.77) | (-0.08) | (0.20) | (1.33) | (0.76) |
| *N* | 374 | 374 | 374 | 374 | 374 |
| *Adj_R²* | 0.020 | 0.402 | 0.294 | 0.315 | 0.244 |

## 6. Conclusions and policy implications

Agricultural geographical indications are an important instrument for advancing rural revitalization and enhancing agricultural economic resilience. Using Chinese provincial panel data from 2008 to 2020, this study constructs an evaluation index system for agricultural economic resilience and examines the impact of agricultural geographical indications on resilience and its transmission mechanisms. The main findings are as follows. First, agricultural geographical indications significantly enhance agricultural economic resilience in the originating region, and this result remains robust after Tobit estimation, sample exclusion, and instrumental variable approaches. Second, geographical indications exert a negative spatial spillover (siphoning effect) on agricultural economic resilience in neighboring regions. Third, the resilience-enhancing effect operates through three channels: brand spillover (higher product prices), industrial agglomeration (greater agglomeration and technological progress), and structural upgrading (improved

rationalization and advancement of the agricultural industrial structure). Based on these findings, we propose the following policy recommendations.

First, continue to promote the construction of agricultural geographical indications and strengthen their brand effect. Governments should fully explore the development potential of regional GI products, improve product quality, and cultivate distinctive agricultural brands. This requires enhancing fiscal capacity, expanding the coverage of inclusive finance, and advancing digital economy development in agriculture.

Second, against the backdrop of heightened external uncertainty and comprehensive rural revitalization, regions should build internal resources and external conditions conducive to agricultural economic resilience based on their natural endowments. Policymakers should increase support for specialty agricultural brands, lower entry barriers for production factors, strengthen investment in agricultural production technology, foster diversified agricultural industrial clusters, and promote the optimization of agricultural industrial structures.

Third, promote differentiated GI development to mitigate the siphoning effect. The negative spatial spillover primarily stems from the similarity of GI products across neighboring regions. To transform competitive pressure into collaborative advantage, neighboring governments should strengthen exchanges and policy coordination, learn from regions with strong GI advantages, develop complementary industries, and build more complete regional industrial and supply chains. Such collaboration can turn the siphoning effect into a synergistic radiation effect that benefits all participating regions.

## Declarations

### Availability of data and materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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### Author contributions statement

NW conceived and designed the study. NW and CZ acquired, analyzed, and interpreted the data. NW and ZT drafted and critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

### Clinical trial number

Not applicable.

### Consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Data availability

The data analyzed for this paper are available from the author upon reasonable request meeting institutional guidelines.

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**Competing interests policy**

The authors declare no competing interests.

**Ethical approval**

This article does not contain any studies with human participants performed by any of the authors.

**Informed consent**

Not applicable.

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