

Agricultural Total Factor Productivity and High-Quality Economic Development in China: Spatial Coupling and Heterogeneous Effects

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Abstract: To reveal the relationship between improvements in agricultural production efficiency and high-quality regional economic development, this study utilizes annual data from 31 provincial-level regions in China spanning 2016 to 2020, resulting in a dataset of 155 province-year observations. First, the Data Envelopment Analysis–Malmquist (DEA–Malmquist) method is employed to measure Agricultural Total Factor Productivity (Agricultural TFP), while the level of high-quality economic development is assessed across dimensions such as economic development, government governance, urban-rural coordination, green and low-carbon development, and shared development. Subsequently, the Global Moran’s I and the Coupling Coordination Degree Model are used to analyze the spatial distribution and the evolution of coordination between the two variables. Furthermore, a Two-way Fixed Effects Model (TWFE), a Spatial Durbin Model (SDM), and a threshold model are applied to examine the overall association, spatial effects, and differences across development stages. The results indicate that the mean high-quality economic development index rose from 0.365 to 0.462, while cumulative Agricultural TFP increased from 1.000 to 1.386; the average coupling coordination degree between the two improved from 0.499 to 0.662. In the TWFE estimation, the coefficient for Agricultural TFP was 0.446 and statistically significant at the 5% level. Decomposition of spatial effects revealed a significant direct effect of 0.368, whereas the indirect effect was 0.297 but not statistically significant. Further threshold testing identified variations in development stages based on per capita GDP, with a threshold value of 11.069; the estimated coefficient for Agricultural TFP was 0.375 (and significant) below this threshold, but the association weakened markedly once the threshold was exceeded. By characterizing the relationship between agricultural productivity and high-quality economic development across temporal, spatial, and developmental dimensions, this study offers a reference for formulating targeted agricultural and regional development policies tailored to regions with varying development foundations.

1. Introduction

Improving the quality of agricultural development involves more than just expanding output scale; it hinges on the more efficient utilization of various factors such as land, labor, machinery, and energy. Agricultural Total Factor Productivity (Agricultural TFP) serves as a key metric in this context, reflecting agricultural production efficiency and technological progress through the lens of aggregate inputs and outputs; consequently, it is frequently used to gauge shifts in the mode of agricultural growth [1,2]. However, gains in agricultural productivity do not automatically translate into a commensurate improvement in the quality of economic development. Factors such as household income, public services, urban-rural integration, resource and environmental conditions, and the level of social equity also shape a region's development quality [3]. This is particularly relevant given the marked disparities across regions regarding resource endowments, industrial foundations, and stages of development; thus, determining whether improvements in agricultural productivity can translate into higher-quality development outcomes requires an analysis that accounts for regional variations and spatial linkages [4,5]. Against this backdrop, it is essential to examine the relationship between agricultural productivity and high-quality economic development, specifically investigating their shared characteristics in terms of temporal evolution and regional distribution. The present study draws on annual data from 31 provincial-level regions in China spanning 2016 to 2020, providing a comprehensive regional dataset for analyzing this relationship.

Existing literature has explored agricultural productivity, regional development levels, and regional disparities from various angles, yet these studies often focus on isolated aspects. For instance, some research concentrates on agricultural production efficiency and its fluctuations, while other studies focus on the comprehensive assessment of high-quality economic development or analyze regional differences through the lenses of regional inequality or spatial linkages [5,6]. By comparison, there is a lack of research that integrates agricultural productivity and multidimensional development quality into a unified analytical framework. In particular, further investigation is needed to determine whether the two exhibit similar regional patterns of change, whether rising agricultural productivity correlates with improvements in local development quality, and how this relationship might shift depending on the region's level of development [7]. Moreover, given the significant disparities among provinces regarding economic foundations, industrial structures, and resource conditions—combined with the potential for spatial spillovers between a region and its neighbors—relying solely on aggregate average changes is insufficient to fully explain these regional characteristics [8]. This study builds upon the original research by addressing the lack of a unified analysis linking productivity, development quality, regional disparities, and spatial connections. Addressing these issues, this paper adopts the overall approach of the original study to analyze the dynamic relationship between agricultural total factor productivity (TFP) and high-quality economic development. First, it comprehensively assesses the level of regional high-quality economic development across dimensions such as economic performance, government governance, urban-rural coordination, green development, and shared development, while employing the Data Envelopment Analysis–Malmquist (DEA–Malmquist) index method to measure changes in agricultural TFP across regions. Subsequently, it uses spatial correlation analysis to examine whether stable agglomeration patterns exist among different regions and employs coupling coordination analysis to observe the degree of synchronous change between agricultural productivity and high-quality economic development [1,6].

On this basis, a Two-way Fixed Effects Model (TWFE) is used to analyze the relationship between agricultural TFP and high-quality economic development, while a Spatial Durbin Model (SDM) is utilized to distinguish between local and neighboring regional effects. Finally, a threshold model is introduced to investigate whether this relationship varies significantly across different stages of development, ensuring the results reflect both overall trends and regional disparities [7,8]. These

methods are derived from the analytical framework of the original study and center on the core relationship between agricultural TFP and high-quality economic development. Compared to studies examining only single-indicator changes, this paper presents the content of the original research through three key aspects. First, it analyzes agricultural TFP and high-quality economic development within a unified framework, linking changes in agricultural productivity efficiency to broader development quality and avoiding the pitfall of equating productivity gains alone with the overall level of development. Second, it considers spatial connections between regions alongside overall changes and integrates coupling coordination analysis with subsequent econometric analysis; this enables the study to not only describe the developmental trajectories of both variables but also determine whether a stable association exists between agricultural TFP and local high-quality economic development. Finally, this paper further distinguishes between intra-regional and inter-regional effects, as well as variations across different stages of development, thereby providing a more nuanced explanation of the diverse ways in which agricultural productivity growth may manifest under varying regional conditions. Building upon the core findings and fundamental conclusions of the original research, this analysis aims to present the relationships among agricultural total factor productivity, high-quality economic development, and regional disparities in a more focused manner, offering a reference for future studies in this field.

2. Data and Methodology

2.1. Data and Variable Description

This study refers to annual data for 31 provincial-level regions in China from 2016 to 2020, comprising 155 province-year observations [9-10]. The indicators are mainly drawn from the China Statistical Yearbook and the China Rural Statistical Yearbook. The high-quality economic development index Y is taken as the dependent variable, cumulative Agricultural Total Factor Productivity (Agricultural TFP) as the core explanatory variable, population density and the share of the primary sector as control variables, and Gross Domestic Product per capita (GDP per capita) as an indicator of the development stage [11-12].

High-quality economic development is assessed from five dimensions: economic performance, government economic governance, urban-rural coordination, green and low-carbon development, and shared development and welfare, covering 16 indicators in total. After the direction of each indicator is unified and the data are standardized, indicator weights are determined according to the information carried by each indicator, and the comprehensive development index is obtained as

$$Y_i = \sum_{j=1}^m w_j z_{ij} \quad (1)$$

where z_{ij} denotes the standardized value of indicator j for observation i , and w_j denotes the corresponding indicator weight. The definitions and measurement methods of the main variables used in the empirical analysis are summarized in Table 1.

Table 1: Main variables and measurement

Variable	Measurement
High-quality economic development	Composite index based on 16 indicators
Agricultural TFP	DEA-Malmquist cumulative index
Population density	Resident population divided by administrative land area
Primary-sector share	Primary-industry value added divided by GDP
GDP per capita	Indicator of the regional development stage

After the variables and their measurements are specified, a dynamic indicator is required to describe changes in agricultural production efficiency. Therefore, the DEA-Malmquist approach is adopted to measure Agricultural TFP.

2.2. Measurement of Agricultural Total Factor Productivity

The Data Envelopment Analysis-Malmquist Index (DEA-Malmquist) method is used to measure changes in Agricultural TFP. This approach does not require a predefined production-function form and can compare changes in production efficiency under multiple inputs [13-14]. The original study uses pesticide use, total power of agricultural machinery, agricultural diesel use, fertilizer use, and agricultural plastic-film use as the main inputs, while the gross value of agriculture, forestry, animal husbandry, and fisheries is used as the output.

The Malmquist productivity index between two adjacent periods is expressed as

$$M_0^{t,t+1} = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \right]^{1/2} \quad (2)$$

Because the Malmquist index measures productivity change between adjacent periods rather than an absolute productivity level, 2016 is used as the common base year and normalized to 1. Cumulative Agricultural TFP in subsequent years is obtained by chaining the adjacent-period indices [15]:

$$TFP_{i,2016} = 1TFP_{i,t} = TFP_{i,t-1}M_{0,i}^{t-1,t}, \quad t = 2017, \dots, 2020 \quad (3)$$

Agricultural TFP describes the temporal change in production efficiency, but comparisons of index levels alone cannot show whether these changes have spatial links. Therefore, spatial dependence and the coordination between Agricultural TFP and high-quality economic development are examined next.

2.3. Spatial Dependence and Coupling Coordination

Global Moran's I is used to examine whether similar levels of Agricultural TFP and high-quality economic development are spatially clustered. A row-standardized provincial contiguity matrix is adopted as the spatial weight matrix, and statistical significance is assessed using 999 random permutations. Global Moran's I is calculated as

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

where n denotes the number of provinces, w_{ij} represents the spatial weight between provinces i and j , x_i and x_j denote the observed values of the variable in provinces i and j , respectively, $\bar{x}$ is the sample mean, and $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all spatial weights.

On this basis, a coupling coordination model is used to evaluate the joint evolution of Agricultural TFP and high-quality economic development. Let U_1 and U_2 denote the processed Agricultural TFP and high-quality development levels, respectively. The coupling degree C represents their relative matching, the comprehensive development index T represents their overall level, and the coupling coordination degree D summarizes their coordination state:

$$C_{it} = \frac{2\sqrt{U_{1,it}U_{2,it}}}{U_{1,it} + U_{2,it}} T_{it} = 0.5U_{1,it} + 0.5U_{2,it} D_{it} = \sqrt{C_{it}T_{it}} \quad (5)$$

The spatial and coordination analyses describe regional patterns and joint evolution, but they do not determine whether Agricultural TFP remains associated with high-quality economic development after regional and temporal differences are controlled. Panel and spatial econometric models are therefore introduced for further examination.

2.4. Econometric Models

A Two-way Fixed Effects Model (TWFE) is first used to control simultaneously for time-invariant regional differences and common annual changes. The model is specified as

$$\ln Y_{it} = \beta \ln TFP_{it} + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (6)$$

where X_{it} denotes the control variables, μ_i is the regional fixed effect, τ_t is the time fixed effect, and ε_{it} is the disturbance term. The coefficient β measures the conditional association between Agricultural TFP and high-quality economic development.

Considering possible spatial links across regions, a Spatial Durbin Model (SDM) is then applied by including spatially lagged terms of both the dependent and explanatory variables:

$$\ln Y_{it} = \rho W \ln Y_{it} + \beta \ln TFP_{it} + \gamma' X_{it} + \theta W \ln TFP_{it} + \eta' W X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (7)$$

This specification allows the Agricultural TFP effect to be separated into a direct effect within the region, an indirect effect transmitted across neighboring regions, and a total effect.

Finally, to examine whether the Agricultural TFP-development relationship changes with the regional development stage, the logarithm of GDP per capita is used as the threshold variable in a single-threshold model:

$$\ln Y_{it} = \beta_1 \ln TFP_{it} I(q_{it} \leq \gamma) + \beta_2 \ln TFP_{it} I(q_{it} > \gamma) + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (8)$$

Here, q_{it} denotes the regional development level, γ is the estimated threshold, and β_1 and β_2 represent the Agricultural TFP-development relationship on the two sides of the threshold. Together, these methods form a compact analytical sequence from productivity measurement and spatial-pattern analysis to overall association and development-stage heterogeneity.

3. Results and Discussion

3.1. Evolution of Agricultural TFP and High-Quality Development

As shown in Fig. 1(a), the distribution of cumulative Agricultural TFP shifted steadily to the right from 2017 to 2020. The provincial mean increased from 1.001 in 2017 to 1.109, 1.245, and 1.386 in the following three years. At the same time, the distribution became broader: the cross-provincial standard deviation rose from 0.076 in 2017 to 0.245 in 2020, while the right tail extended beyond 2.0. This pattern indicates that productivity improved overall, but the cumulative gains became increasingly uneven across provinces.

Fig. 1(b) shows a different pattern for high-quality economic development. Its mean increased from 0.365 in 2016 to 0.462 in 2020, an increase of approximately 26.5%, while the standard deviation fell from 0.149 to 0.123. The density curves moved to the right and became more concentrated around the main peak. Therefore, the two indicators both improved over the sample period, but their cross-provincial distributions evolved in opposite directions: cumulative Agricultural TFP became more dispersed, whereas high-quality development showed a clearer tendency toward convergence.

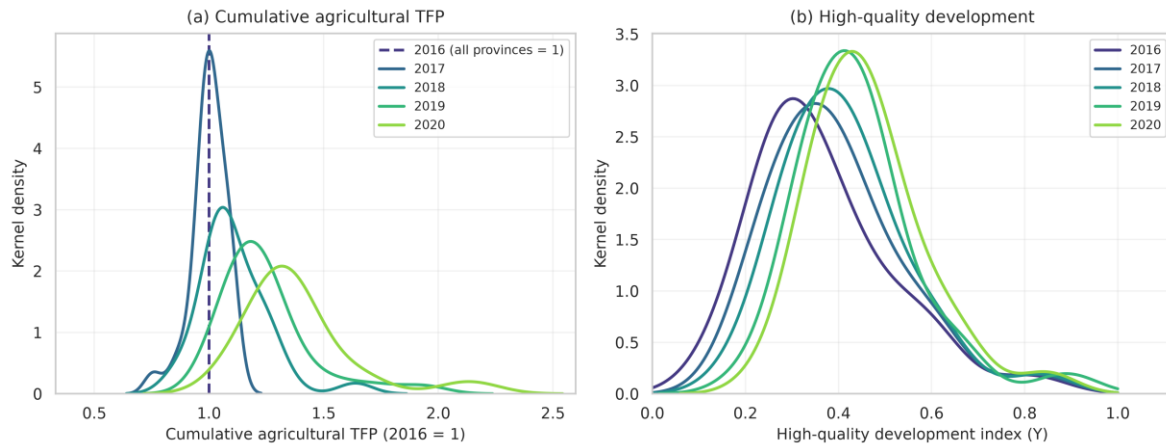


Figure 1: Kernel density distributions of cumulative Agricultural TFP and high-quality economic development, 2016–2020.

3.2. Spatial Dependence Analysis

Fig. 2(a) shows that the global Moran’s I values of high-quality economic development were 0.402, 0.378, 0.365, 0.236, and 0.356 from 2016 to 2020, respectively. All annual statistics were significant at the 5% level ($p < 0.05$). The consistently positive values indicate that provinces with similar development levels tended to be spatially clustered. However, the index declined from 0.402 in 2016 to 0.236 in 2019 before recovering to 0.356 in 2020, showing persistent spatial dependence rather than a continuously strengthening pattern.

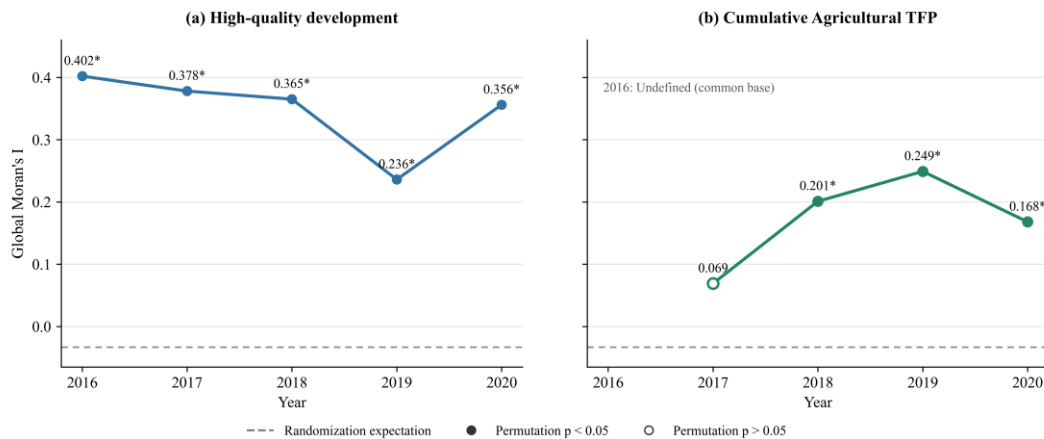


Fig. 2: Global Moran’s I for Agricultural TFP and high-quality economic development

As shown in Fig. 2(b), spatial dependence in cumulative Agricultural TFP emerged later. For cumulative Agricultural TFP, spatial dependence emerged later. The statistic is undefined in 2016 because all provinces share the same base value of 1. The global Moran’s I was only 0.069 in 2017 and was not statistically significant. It increased to 0.201 in 2018, 0.249 in 2019, and 0.168 in 2020, with significance obtained from 2018 onward. The peak in 2019 followed by a decline in 2020 suggests that the spatial association of productivity growth was present but not monotonic. Compared with Agricultural TFP, the spatial clustering of high-quality development was more persistent throughout the sample period.

3.3. Coupling Coordination between the Two Systems

Fig. 3 shows a clear upward trend in the coordination between the two systems. The national mean coupling coordination degree increased only slightly from 0.499 in 2016 to 0.504 in 2017, but then rose to 0.556, 0.614, and 0.662 in 2018–2020. The provincial range also shifted upward, from 0.393–0.619 in 2016 to 0.578–0.767 in 2020, indicating that the improvement was not confined to a small number of provinces.

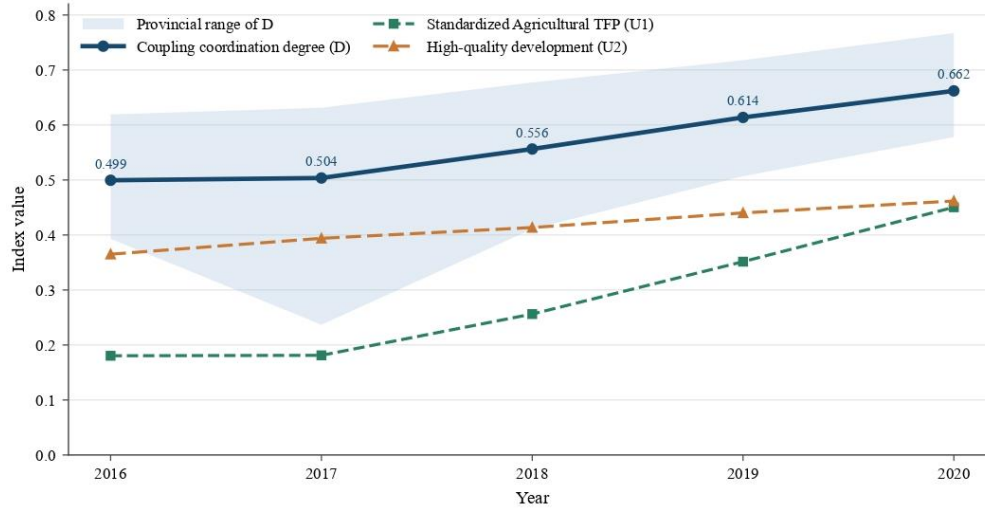


Fig. 3: Evolution of Agricultural TFP, high-quality development, and coupling coordination

The standardized Agricultural TFP subsystem increased from 0.180 to 0.450, while the high-quality development subsystem rose from 0.365 to 0.462. Over the same period, the mean coupling degree remained within $C = 0.900 - 0.969$, indicating a consistently high degree of relative matching. The rise in the coordination degree therefore mainly reflected higher overall subsystem levels and a narrower gap between them, rather than a sudden change in their relative coupling structure.

The annual transition also became more pronounced after 2017. The coordination degree increased by only 0.005 between 2016 and 2017, but by a cumulative 0.158 from 2017 to 2020. By 2020, 23 provinces had reached the primary coordination level and 6 had entered intermediate coordination, while only 2 remained barely coordinated. This distribution confirms that the improvement observed in the national mean was accompanied by a broad upward shift in provincial coordination levels.

3.4. Overall and Spatial Effects of Agricultural TFP

To assess whether the estimated relationship is sensitive to alternative treatments, the baseline result is compared with several robustness specifications. The main estimates are summarized in Table 2.

Table 2: Main estimates for Agricultural TFP

Specification	Coefficient	Std. error	p-value
Two-way fixed effects	0.446	0.194	0.029
1% winsorization	0.382	0.149	0.016
Excluding municipalities	0.493	0.204	0.023
Lagged Agricultural TFP	0.255	0.154	0.109
Driscoll–Kraay standard errors	0.446	0.091	<0.001

The baseline two-way fixed-effects estimate is 0.446 and is significant at the 5% level. After 1%

winsorization and after excluding municipalities, the coefficients remain positive at 0.382 and 0.493, respectively. The lagged specification also remains positive, although its statistical significance weakens. The consistency in coefficient direction across these treatments indicates a relatively stable positive association between Agricultural TFP and high-quality economic development within provinces.

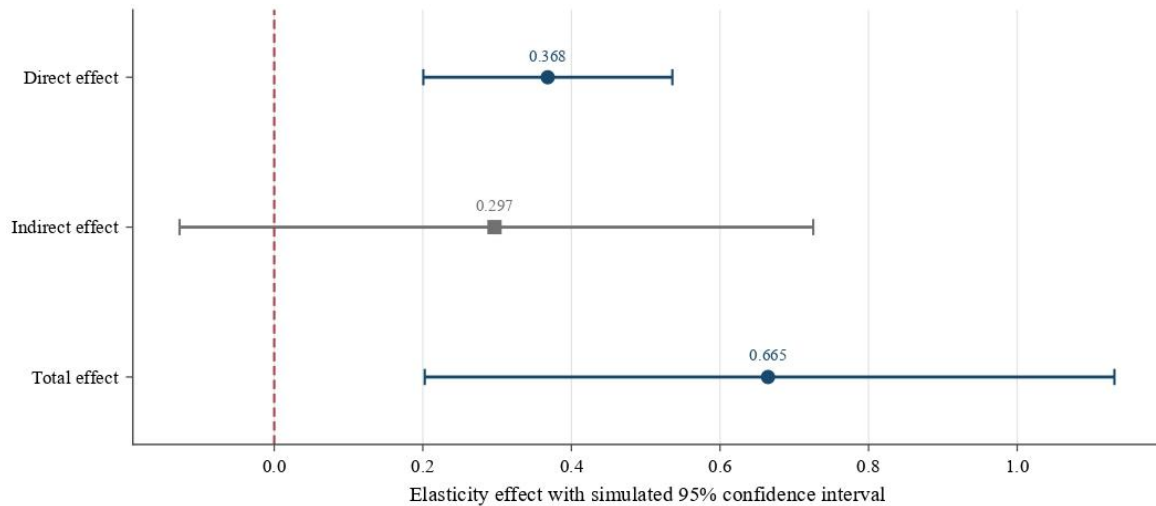


Fig. 4. Spatial impact decomposition of Agricultural TFP

The spatial impact decomposition provides a more detailed view of the regional source of this relationship. The direct effect is 0.368 ($p < 0.001$), indicating a significant positive association within the same province. The indirect effect is 0.297 ($p = 0.164$), and its confidence interval crosses zero, so a stable cross-provincial transmission effect cannot be established. The total effect reaches 0.665 ($p = 0.004$). As shown by the confidence intervals in Fig. 4, the significance of the total effect is driven primarily by the direct component rather than by the neighboring-province effect.

This distinction is important when the result is compared with the Moran analysis above. Spatial clustering indicates that neighboring provinces may display similar values, but such clustering does not by itself imply that productivity gains in one province produce a statistically detectable improvement in the development quality of adjacent provinces.

3.5. Development-Stage Heterogeneity

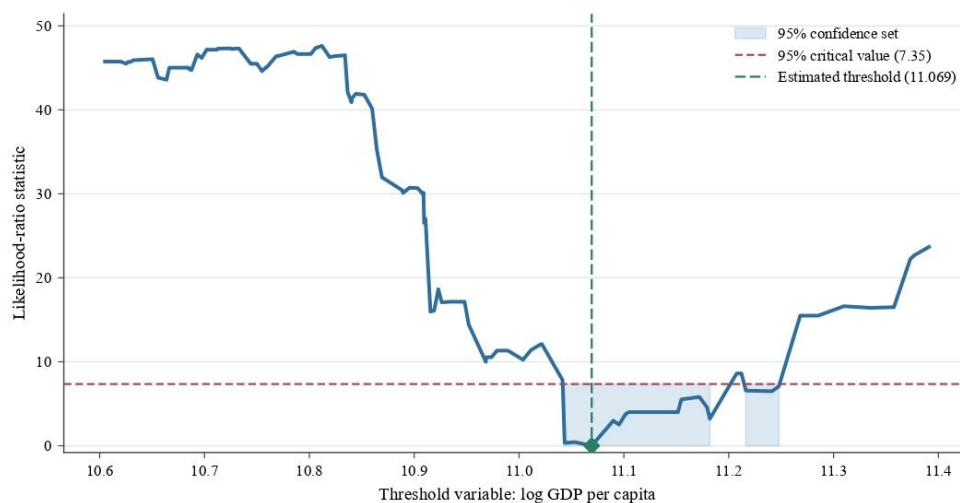


Fig. 5. Likelihood-ratio profile for the GDP-per-capita threshold

The likelihood-ratio curve in Fig. 5 reaches its minimum at a threshold of 11.069, corresponding to GDP per capita of approximately RMB 64,171. The Sup-F statistic is 47.646, and the 499-replication wild-cluster bootstrap gives $p = 0.002$, providing evidence that the association between Agricultural TFP and high-quality development differs across development stages.

At or below the threshold, the Agricultural TFP coefficient is 0.375 ($p = 0.036$), showing a statistically significant positive association. Above the threshold, the coefficient changes to -0.344 ($p = 0.133$), but the estimate is not statistically significant. The high-stage result should therefore be interpreted as an attenuation and loss of significance rather than as evidence that higher Agricultural TFP reduces high-quality development.

The threshold pattern suggests that improvements in agricultural production efficiency are more closely associated with development quality where income and resource constraints remain relatively stronger. At higher development levels, innovation, public services, human capital, and environmental governance may become more important in shaping development quality. Thus, the relationship between Agricultural TFP and high-quality development varies in strength across development stages rather than remaining constant across all provinces.

4. Conclusion

This paper analyzes the relationship between agricultural total factor productivity (TFP) and high-quality economic development, conducting a comprehensive examination across dimensions such as temporal evolution, spatial correlation, coordination status, and developmental stage disparities. The findings indicate a generally positive association between improvements in agricultural production efficiency and high-quality economic development; however, this relationship exhibits distinct regional variations and stage-specific characteristics, meaning it does not manifest uniformly across all regions. While spatial agglomeration is evident across different regions, spatial correlation does not equate to stable cross-regional transmission. Consequently, in practice, efforts to enhance agricultural productivity should be integrated with regional industrial foundations, resource endowments, public services, and governance capabilities. Regions with weaker development foundations should prioritize supporting factors such as agricultural technology extension, infrastructure, human capital, and market services. Conversely, regions with higher levels of development should further leverage technological innovation, modern service industries, and green governance to more effectively translate agricultural production efficiency gains into comprehensive development quality.

This study has certain limitations. The relatively short timeframe may mean that some long-term trends have not yet fully emerged, and the use of a fixed base year for agricultural TFP calculation could influence the assessment of early-stage disparities. Additionally, spatial analysis results are sensitive to the specification of spatial weights, and there is an inherent link between the developmental stage variable and the evaluation system for high-quality economic development. Therefore, the current findings serve better as a basis for analyzing statistical relationships and regional differences rather than for establishing strict causal inferences. Future research could extend the study period, refine agricultural input and output indicators, employ alternative spatial specifications for cross-validation, and utilize more robust identification methods. Such efforts would facilitate a deeper analysis of the specific pathways through which agricultural productivity influences high-quality economic development, thereby providing a reference for formulating targeted development strategies for different types of regions.

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