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Yongqing Zhu

Inner Mongolia Agricultural University

Fengtong Yao

yfengt63@163.com

Inner Mongolia Agricultural University

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The Spatial-Temporal Effects of Knowledge Spillovers and R&D Investment on Regional Agricultural Productivity: An Empirical Analysis Based on Province-level Panel Data from China

Yongqing Zhu¹, Fengtong Yao^{2*}

Abstract

There is a broad consensus that R&D investment serves as a catalyst for technological advancement. However, the impact of R&D investment on Total Factor Productivity (TFP) varies significantly across research entities, particularly for agricultural Total Factor Productivity (ATFP), where the pronounced spatial spillover effects of knowledge—stemming from agriculture's strong geographical characteristics—complicate R&D's influence on ATFP. This study employs per capita R&D investment across different research entities, which reflects both capital and personnel inputs while distinguishing among entities to assess their temporal and spatial impacts on agricultural productivity. Using provincial panel data (1998–2022) and a progressive analytical approach, static and dynamic spatial econometric models are applied. Considering the heterogeneity of agricultural geographical production conditions and economic conditions, a novel agricultural production geography-based weight matrix is constructed. The results reveal that, statically, Research and Development Institutions (RDI) and Higher Education (HE) show strong direct effects but lack spatial externalities, instead exerting crowding-out effects on ATFP. Dynamically, HE exhibits initial inhibitory and subsequent promoting effects on ATFP, while RDI demonstrate strong negative externalities in the long term. It uncovers the unique impact pathways of R&D investment on ATFP, offering insights for optimizing regional innovation resource distribution. It highlights the need for tailored support policies suited to distinct research institutions, stresses the significance of temporal-spatial coordination in R&D investment, and calls for strengthening cross-regional knowledge-sharing mechanisms to fully realize R&D investment's potential in boosting agricultural innovation.

Keywords Dynamic spatial Durbin model; Static spatial Durbin model; R&D Investment; Agricultural total factor productivity; Spatial spillovers.

1. Introduction

Total factor productivity (TFP), a key indicator of technological innovation, has been central to economic research. Endogenous growth theory (Aghion & Howitt, 1992) asserts technological progress as the main driver of TFP growth. While R&D investment is acknowledged as a vital innovation source influencing TFP through knowledge accumulation, the empirical link between research inputs and productivity remains debated. Traditional views suggest a positive R&D-TFP correlation, but contradictory findings (e.g., Li, 2010; Chen, 2010) reporting negative impacts underscore the need for deeper exploration of this complex relationship.

Based on existing relevant research, firstly, a comprehensive review of the literature from the past five years reveals that studies in related fields predominantly focus on the enterprise level, particularly enterprises in the industrial sector. In the context of globalization over the past three decades, multinational corporations have played a crucial role in technology spillovers over the past few decades, leading many studies to concentrate on the field of transnational capital.

¹ Inner Mongolia Agricultural University, College of Economics and Management, Hohhot, Inner Mongolia, P. R. China E-mail: zeechu136@hotmail.com

² Corresponding Author: Inner Mongolia Agricultural University, College of Economics and Management, Hohhot, Inner Mongolia, P. R. China E-mail: yfengt63@163.com

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In contrast, agriculture has garnered relatively limited attention, with a notable absence of research on agricultural total factor productivity (ATFP) grounded in a country's specific agricultural scientific research conditions. Crucially, as an evolving econometric approach, spatial econometrics is still developing in the study of dynamic spaces that account for temporal trends, and its application in this field remains scarce, with existing literature rarely considering both aspects comprehensively. Notably, scientific research activities exhibit time-lag effects; while possessing spatial characteristics, they should also incorporate temporal attributes. Furthermore, the specification of the spatial weight matrices, a pivotal component of spatial econometrics, constitutes the core of its methodology. Traditional studies frequently directly measure the relationship between scientific research input and technological development; even when some employ geographical adjacency or economic distance matrices, these settings fail to accurately capture the unique nature of agricultural knowledge spillovers. Lastly, some literature tends to treat research entities as homogeneous units, overlooking the heterogeneity in research efficiency among different scientific research institutions, such as universities, research institutes, and corporate R&D centers. As a country with highly concentrated scientific research resources, China's innovation system exhibits significant spatial imbalance, a characteristic that is particularly prominent in the agricultural sector. There has been no overall convergence in agricultural productivity levels across China. This implies that backward regions still need to make extra efforts to catch up with advanced regions (Sun et al., 2019).

Addressing these research gaps, this study examines the impact of R&D investment by different research entities including Research and Development Institutions (RDI) and Higher Education (HE) sectors on ATFP in China's unique institutional context. Using provincial panel data from 1998 to 2022, we employ a progressive analytical approach: Initial cluster analysis reveals significant spatial disparities between RDI/HE indicators and ATFP growth patterns. Despite the 25-year panel data exhibiting non-ideal time-series properties (as confirmed by unit root and cointegration tests), these characteristics provide a theoretical foundation for spatial dependence analysis. Subsequent spatial econometric diagnostics consistently validate the data's suitability for spatial modeling. Followed by spatial econometric analysis both in static and dynamic levels to verify knowledge spillover effects in both temporal and spatial dimensions.

This study boasts the following innovative aspects: Firstly, we employ a cutting-edge dynamic spatial econometric model (dynamic spatial Durbin model) to conduct an in-depth analysis of the allocation efficiency of agricultural scientific research resources across geographical units and over dynamic time horizons, as well as their differentiated impacts on ATFP. A comparative analysis with static spatial models is also performed, thereby filling a gap in current research. Secondly, in terms of methodology, this study innovatively constructs a spatial weight matrix based on China's comprehensive agricultural regionalization map, taking into account ecological similarity and agricultural technology adaptability, which better aligns with the actual diffusion patterns of agricultural scientific research. Thirdly, from the perspective of the impact of per capita R&D investment on agricultural technological innovation, this study systematically analyzes the differences in R&D efficiency among various scientific research entities, offering a new perspective for understanding the efficiency of scientific research resource allocation.

This study makes three key academic contributions: First, theoretically, it enhances understanding of the relationship between R&D investment and ATFP by clarifying temporal and spatial efficiency differentials among diverse research entities. Second, methodologically, it develops a spatial weight matrix incorporating agricultural geographic characteristics, offering a novel analytical framework for related research. Third, by systematically analyzing the complex interplay between R&D investment and ATFP under China's unique context, this research not only expands the application scope of spatial econometrics but also offers valuable insights for innovation policy design in developing countries.

2. Literature review

TFP, a fundamental metric for assessing economic growth quality, has long been a central focus in economic research. Endogenous growth theory (Romer, 1990) establishes knowledge capital accumulation as a key driver of TFP

enhancement, while the development of spatial econometrics has provided new analytical frameworks for quantifying the spatial dimensions of knowledge spillovers.

Current methodologies for measuring TFP spillover effects fall into three main categories: The first employs proxy variable techniques, utilizing external investment, industry-specific shares of Foreign Direct Investment (FDI), or foreign R&D data as indirect indicators of knowledge diffusion (Huang et al., 2019; Bournakis & Tsionas, 2022; Herzer, 2022). The second approach relies on industrial linkage analysis, integrating sub-industry correlation coefficients with firm-level R&D data to quantify spillover effects (Yasin et al., 2024). The third directly applies spatial econometric models, leveraging spatial weight matrices to capture spatial dependencies (Zhang et al., 2025; Dai et al., 2022; Tientao et al., 2014; Liu & Zhang, 2013; Scherngell et al., 2013).

From the perspective of spatial econometric model evolution, traditional frameworks primarily address spatial dependencies in cross-sectional data, whereas dynamic spatial models enable unified analysis of both spatial and temporal dimensions. Currently, static spatial econometric models dominate as the mainstream approach, while dynamic methods—a frontier in spatial econometrics—remain under development, primarily applied to analyze growth and convergence patterns across countries or regions (Ertur & Koch, 2007; Elhorst et al., 2010; Elhorst, 2014).

Regarding early research on the identification and quantification of spatial spillover effects, R&D investment spillovers exhibit pronounced geographical attenuation (Jian, 2008; Su, 2006). Gonçalves et al. (2021) found that domestic knowledge stock exerts a significantly stronger direct impact on TFP than indirect effects, with domestic knowledge stock positively influencing TFP while external knowledge spillovers demonstrate negative impacts.

Moreover, analysis of the heterogeneity in development stages reveals that R&D spillover spatial elasticity is substantially higher in high-income countries compared to middle- and low-income counterparts. Herzer (2022) incorporated time dummy variables to assess domestic and foreign R&D impacts on developing countries' TFP, finding that middle-income countries exhibit strong positive domestic R&D effects on TFP (elasticity range: 0.243-0.310), whereas low-income countries demonstrate weaker impacts with lower elasticity estimates.

Industry-specific comparative studies present more complex patterns. Scherngell et al. (2013) reported that TFP in Chinese manufacturing provinces yields a direct effect of 0.025 and indirect effect of 0.031 on TFP. Dai (2022) found technology enterprises' TFP to be most responsive to knowledge spillovers (elasticity around 0.176), followed by internal R&D (0.129) and R&D cooperation (0.036), with indirect effects exceeding direct ones. Tientao et al. (2014) and Zhao & Hu (2012) noted that, from their respective research perspectives and hierarchical levels, R&D investment exerts a significantly positive impact on TFP in both local and spatially correlated regions. However, the findings of Li (2010) and Chen (2010) indeed challenge the conventional belief in a positive correlation between R&D investment and total factor productivity growth. While there are divergences in these findings and analytical perspectives, an overall consistent trend is evident. The observed industry disparities may be attributed to variations in knowledge codification levels and absorptive capacities.

However, current research demonstrates notable limitations and confronts emerging challenges. From an industrial perspective, the existing literature predominantly focuses on manufacturing and information technology sectors, with agriculture—a cornerstone of national economies—receiving comparatively limited scholarly attention. Meanwhile, from an economic hierarchy standpoint, most studies revolve around the micro - level of enterprises. Agriculture, as a fundamental industry in the national economy, deserves its own academic prominence, yet research in this area remains scarce. Secondly, while substantial research (e.g., Huang et al., 2019; Bournakis & Tsionas, 2022) has analyzed spatial spillover effects of R&D investments, few studies have systematically compared research efficiency across core scientific institutions such as universities and research institutes. Among accessible literature, only Anselin et al.'s (2000) early study examined the impact of scientific research investment by U.S. universities in the 1980s on four industries. This gap becomes particularly pronounced under research organizational modes like "Concentration of advantageous resources" phenomena, where spatial resource allocation efficiency remains underexplored. Moreover, the dynamic interplay

between temporal and spatial dependencies in agricultural technological innovation across different research entities has not been adequately investigated. Finally, methodological controversies persist regarding weight matrix specifications. Given agriculture's strong spatial dependence, geographical factors warrant special consideration. While geographic adjacency matrices dominate current research, Liu et al. (2021) revealed that such simplifications systematically underestimate spillover effects by 27%, highlighting the need for more nuanced spatial modeling approaches.

3. Theoretical framework and research hypotheses

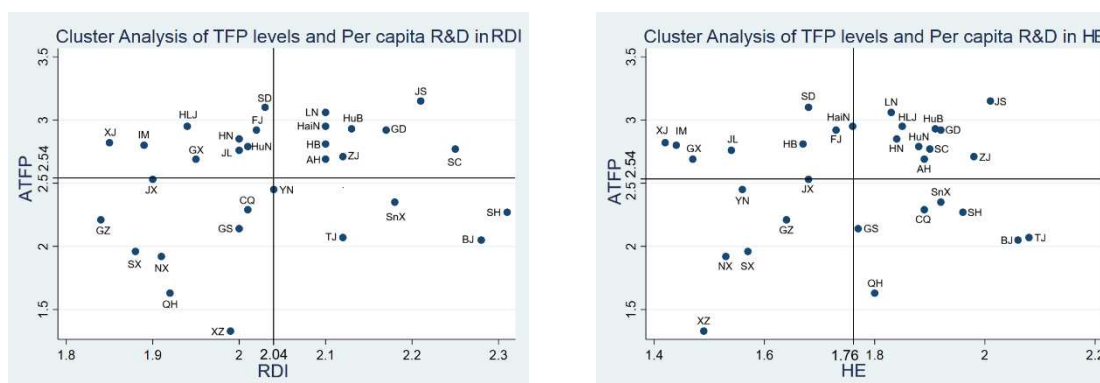
Hypothesis 1: For both static and long-term dynamic direct effects, the ratio of RDI's direct effect to HE's direct effect should be at least equal to their corresponding per capita R&D investment ratio (RDI/HE).

R&D activities directly contribute to knowledge accumulation, a key driver of technological progress and economic growth, and most directly promote local technological development. Although some studies (e.g., Yu et al., 2021; Li, 2010; Chen, 2010) have reported cases where R&D investment fails to enhance productivity, with certain issues remaining unverified, a greater body of research ((e.g., Nadiri, 1993; Higon, 2007) indicates that the positive impacts of technological innovation or internal R&D investment primarily benefit the investing entities themselves. Early work by Higon (2007) reviewed prior literature and estimated R&D's contribute elasticity on TFP to range from 0.015 to 0.37. Consequently, the direct effect of R&D investment should be positive. Under constant returns to scale, R&D investment and TFP growth should exhibit proportional changes. Thus, the baseline for effective R&D measurement should at least manifest as a linear pattern. We therefore propose the following efficiency criteria: When the direct effect ratio (RDI/HE) exceeds the investment ratio, it indicates effective research systems capable of generating supra-linear TFP growth. When the direct effect ratio falls below the investment ratio coupled with negative spillovers, it signifies significant research inefficiency - failing to achieve even linear scaling of productivity gains while potentially creating crowding-out effects on spatial correlation regions' TFP.

Hypothesis 2: Building on cluster analysis showed below, we posit that China's concentrated R&D resource allocation leads to a spatial mismatch between agricultural research hubs and major agricultural provinces. Consequently, both RDI and HE institutions should demonstrate significantly positive spillover effects (indirect effects) in both static and long-term dynamic models.

The cluster analysis clearly reveals notable spatial imbalances in the growth distribution of per capita R&D investment and ATRP across China's provinces, with two main types of research institutions showing pronounced disparities. Scientific research resources are predominantly concentrated in developed regions and major administrative/economic hubs, which are not necessarily major agricultural provinces. This concentration primarily drives such imbalances while simultaneously creating conditions for R&D resource spillovers.

Figure 1. Cluster Analysis of ATRP and Per Capita R&D Investment



Source: Authors own work

Academic research on spillover effects has a long history. Robert Lucas posited that human capital generates spillover effects through mutual learning, exhibiting strong positive externalities proportional to its intensity. Scholars have also explored the mechanisms of spillover: Kokko (1994) attributed technological knowledge spillovers to human capital imitation, information dissemination, and inter-firm competition; Wang (1992) and Blomstrom (2001) emphasized how decision-making behaviors of local firms and multinational subsidiaries drive spatial diffusion of spillovers; while Keller et al. (2004) argued that spillovers result from spatial diffusion, linking disconnected regions into an integrated system with structural interactions. These studies revealed that scientific research activities often exhibit pronounced externalities, a characteristic particularly evident at the macroeconomic level. From a static spatial perspective, all research institutions should exhibit positive spillovers. Moreover, given the well-documented time-lagged nature of research impacts, all entities should contribute positively to ATFP in the long run through spatial spillovers.

Hypothesis 3: In dynamic models, RDI should exhibit positive direct and indirect effects in the short term, while HE should demonstrate negative direct and indirect effects. These hypotheses are applied to analyze short-term dynamic spatial interactions.

Based on the comparative mechanism of R&D benefits and costs, technological knowledge production can be categorized into market-driven (pricing > marginal cost) and publicly supported (pricing ≤ marginal cost) modes. Given China's R&D division of labor, RDI aligns more with market-driven mode, emphasizing short-term efficacy. Consequently, RDI is expected to yield positive impacts on both local and spatially correlated regions in the short term. Conversely, HE leans toward publicly supported mode, prioritizing long-term outcomes. Thus, HE may strain public resources in the short term, resulting in negative effects on local and spatially correlated regions. Dynamic spatial models, which incorporate both spatial and temporal dimensions, are well-suited to capture these divergent patterns across research entities.

Hypothesis 4: Under the agricultural geography-based weight matrix (GM) framework, the spatial correlation between ATFP and per capita agricultural R&D investment will be stronger than that observed using spatial adjacency weight matrices (AM).

This hypothesis will be empirically validated through three key dimensions: More statistically significant correlation test results from the GM. Superior model fit and higher coefficient significance in spatial regression models employing this matrix. Greater elasticity of spatial spillover effects for both research institutions.

Methodological justification stems from Zhu's (2024) findings demonstrating that ATFP exhibits not only adjacency-based correlations but also significant agricultural geography-based spatial dependencies. Consequently, our analysis incorporates both AM and GM to comprehensively assess the impact of per capita R&D investment on ATFP.

4. The model and econometric methodology

4.1. The Model

Endogenous growth theory posits technological progress as the fundamental driver of economic expansion. This theoretical framework, particularly when examining the knowledge-innovation-growth nexus, highlights technological advancement as the critical determinant of sustained long-term growth (Griliches, 1979). Empirical evidence consistently demonstrates that R&D investments significantly enhance innovation output, with a positive correlation between innovation and knowledge stock - a manifestation of knowledge spillover effects. Audretsch et al. (2004) further substantiate the pronounced externalities inherent in research activities, especially at the macroeconomic level.

Building upon the Cobb-Douglas production framework and the conventional definition of TFP, we derive the ATFP function as:

$$\ln ATFP_{it} = \varphi + \theta \ln RD_{it} + \lambda \ln X_{it} + \varepsilon_{it} \quad (1)$$

where ATFP serves as the technology innovation indicator, RD represents per capita R&D investment by major institutions, and X denotes other determinants of ATFP.

4.2. Data

The dataset was compiled from authoritative sources including: China Statistical Yearbook, China Statistical Yearbook on Science and Technology, and Provincial statistical bulletins on national economic and social development. To ensure cross-temporal comparability, all capital-related variables were deflated to 1998 constant prices using producer price indices (PPI).

4.2.1. Dependent Variable

TFP, a pivotal metric for technological progress, is typically measured using four principal approaches: production function methods, control function approaches, stochastic frontier analysis (SFA), and data envelopment analysis (DEA). These methodologies quantify the "residual" component of output unexplained by conventional input factors, thereby revealing the dynamic characteristics of technological advancement.

While production function methods are widely applied at macro and meso levels, their estimates often exhibit substantial volatility, compromising trend analysis reliability. The control function approach proposed by Olley and Pakes (1996) addresses this endogeneity concern through proxy variables, yielding more robust TFP estimates across the micro levels. This method demonstrates superior temporal consistency and statistical significance in TFP measurement. This study adopts the Olley-Pakes (OP) method with agricultural electricity consumption as the proxy variable to estimate ATFP, which serves as our dependent variable. The TFP estimation employs provincial gross agricultural output value as the outputs, while inputs consist of primary sector employment (calculated using rural employment structure and industry shares) and agricultural investment. Agricultural electricity consumption from provincial energy expenditure data serves as the proxy variable.

4.2.2. Independent Variable

Agricultural technological innovation exhibits quintessential public good characteristics, with its non-rivalrous and non-excludable nature fostering a diversified innovation ecosystem. Within China's agricultural innovation system, RDI and HE constitute the core R&D entities. While agricultural enterprises are primarily viewed as suppliers of primary products, their operations encompass value-added processes like agricultural product processing. However, per the classification in China Statistical Yearbook on Science and Technology, such enterprises fall under industrial statistics and are thus excluded from this study. Equally noteworthy is the "learning-by-doing" effect in agricultural production (LBDE), which serves as another vital source of technological progress.

The intensity of technology spillovers critically depends on human capital as a key determinant. The effectiveness of technology diffusion is principally contingent upon the absorptive capacity of recipients, which demonstrates a significant positive correlation with human capital levels (Shahnazi, 2021; Zhang et al., 2023; Liu & Zhang, 2013). To ensure effective technology assimilation, a systematic framework incorporating innovation capacity building, policy environment optimization, and human capital accumulation is essential. For agriculture, particularly crucial is farmers' human capital - the micro-foundation of agricultural production - whose quality directly determines technology adoption efficiency and consequently emerges as a pivotal determinant of ATFP.

In summary, ATFP is primarily determined by four key drivers: (1) per capita agricultural R&D investment in RDI, (2) per capita agricultural R&D investment in HE, (3) LBDE, and (4) farmer human capital as measured by educational attainment.

For RDI, we calculate per capita agricultural R&D investment (in thousand yuan per researcher) by adjusting total expenditure using the proportion of agricultural sciences funding within natural sciences expenditures, then calibrating for human capital input through the share of agricultural researchers among total scientists and engineers. HE' R&D input adopts a more dynamic full-time equivalent (FTE) approach, where per capita investment (in thousand yuan per FTE per year) is derived by dividing total agricultural research funding by the proportion of agricultural science researchers within STEM fields.

The measurement of industrial learning-by-doing effects by developing an innovative "labor efficiency" proxy

variable grounded in Arrow's (1962) theoretical framework. Departing from Chen et al.'s (2005) untested theoretical model and the operationally limited "production years" metric employed in micro-level studies, our approach quantifies practical knowledge accumulation through price-deflated gross output value of agriculture, forestry, animal husbandry, and fishery divided by primary sector labor input.

Farmer human capital is measured via average years of schooling, calculated as: (illiterate population $\times$ 0) + (primary education $\times$ 6) + (junior secondary $\times$ 9) + (senior secondary $\times$ 12) + (tertiary education $\times$ 16). This indicator selection is consistent with arrow (1962)'s theoretical framework on human capital and the measurement paradigm of existing research.

4.2.3. Setting of Space Weight Matrix

The foundation of spatial econometric analysis lies in the precise specification of spatial interdependence among research units, which is quantitatively represented through spatial weight matrices. Conventional approaches treat these matrices as exogenous, containing predetermined information about interregional spatial relationships. Traditional spatial weight matrices commonly include geographic distance, spatial adjacency, and economic distance matrices (e.g., Scherngell et al., 2023; Li et al., 2025), with specialized matrices such as trade volume (Tientao et al., 2014) and technological distance (Liu & Zhang, 2013) matrices constructed based on specific research perspectives. This study employs a dual-matrix approach: first adopting a standard administrative-boundary-based contiguity matrix (AM), then innovatively constructing a specialized weight matrix that captures agricultural production geography similarity (GM).

(1) Spatial Adjacency Weight Matrix

For the AM, we implement the Rook contiguity criterion where $am_{ij}=1$ indicates shared boundaries between geographic units and $am_{ij}=0$ otherwise. The matrix structure follows standard spatial econometric specifications, with diagonal elements set to zero by convention.

$$AM = \begin{bmatrix} am_{11} & \cdots & am_{1j} \\ \vdots & \ddots & \vdots \\ am_{i1} & \cdots & am_{ij} \end{bmatrix} \quad (2)$$

(2) Agricultural Geography-based Weight Matrix

The spatial heterogeneity of agricultural production manifests through two fundamental dimensions: natural endowments and socioeconomic conditions. While natural factors delineate ecological suitability boundaries for crop cultivation, socioeconomic characteristics shape resource allocation patterns and production organization. This heterogeneity exhibits systematic spatial patterns - maintaining diversity at macro scales while demonstrating relative homogeneity within localized areas.

Building upon the comprehensive agricultural regionalization map from "Agricultural Natural Resources and Regional Development of China", we construct a novel spatial weight matrix incorporating nine distinct agricultural regions. These regions reflect integrated natural geographic and socioeconomic development characteristics: Northeast (include Heilongjiang, Jilin, Liaoning, Inner Mongolia); Inner Mongolia-Great Wall Corridor (include Inner Mongolia, Hebei, Beijing, Shanxi, Shaanxi, Ningxia); Huang-Huai-Hai Plain (include Beijing, Tianjin, Shandong, Hebei, Henan, Jiangsu, Anhui); Loess Plateau (include Shanxi, Shaanxi, Henan, Gansu, Qinghai, Ningxia, Hebei); Middle-Lower Yangtze (include Henan, Jiangsu, Anhui, Hubei, Hunan, Shanghai, Zhejiang, Jiangxi, Fujian, Guangdong, Guangxi); Southwest (include Guizhou, Yunnan, Sichuan, Gansu, Shaanxi, Hubei, Hunan, Guangxi, Henan, Chongqing); South China (include Hainan, Fujian, Guangdong, Guangxi, Yunnan); Gansu-Xinjiang (include Xinjiang, Gansu, Ningxia, Inner Mongolia); and Qinghai-Tibet (include Tibet, Qinghai, Gansu, Sichuan, Yunnan).

Figure 2. Comprehensive Agricultural Regionalization Map of China



Comprehensive Agricultural Regionalization Map of China

Source: Agricultural Natural Resources and Regional Development of China

The GM is constructed based on China's nine comprehensive agricultural regions showed above. This matrix specification captures the fundamental spatial heterogeneity in agricultural production, where province pairs within the same agricultural region ($gm_{ij}=1$) share homogeneous natural conditions and socioeconomic foundations, while inter-zone province pairs ($gm_{ij}=0$) exhibit significant agricultural production heterogeneity.

$$GM = \begin{bmatrix} gm_{11} & \cdots & gm_{1j} \\ \vdots & \ddots & \vdots \\ gm_{i1} & \cdots & gm_{ij} \end{bmatrix} \quad (3)$$

4.3. Econometric methodology

4.3.1. Unit Root Tests and Cointegration Tests for Long Panel Data

The complex data-generating mechanisms and endogeneity issues inherent in macroeconomic variables render traditional OLS estimation inadequate for macro-level analysis, while pure cross-sectional or time-series data often suffer from multicollinearity and autocorrelation problems. To address these limitations, this study implements a rigorous panel data testing procedure. We first apply multiple unit root tests (LLC, Breitung, and Hadri LM tests) followed by various cointegration tests (Pedroni and Westerlund tests) to systematically diagnose data stationarity. These tests identify potential time-dependent characteristics - whether statistical properties exhibit systematic temporal variations - thereby preventing spurious regression problems. The application of multiple complementary tests ensures the robustness of subsequent model specifications.

The panel model incorporating Δ transformations is specified as follows:

$$\Delta Y_{it} = \delta Y_{i,t-1} + \zeta'_{it} \gamma_i + \varepsilon_{it} \quad (4)$$

Where Y denote the variable under unit root testing, where ε_{it} represents a stationary disturbance term and $\zeta'_{it} \gamma_i$ captures panel-specific means, with $\delta_i \equiv \rho_i - 1$. The null hypothesis for panel unit root tests posits $H_0: \delta_i = 0, \forall i$, against the alternative $H_1: \delta_i < 0$. Notably, the Hadri LM test accommodates unbalanced panels with heterogeneous

autoregressive coefficients across units, while both LLC and Breitung tests assume homogeneous autoregressive parameters.

The LLC test addresses individual heterogeneity and serial correlation through a three-stage estimation procedure: deriving standardized residuals via auxiliary regression, followed by pooled regression modeling. This method requires the time dimension (T) to grow faster than the cross-section dimension (n) and assumes cross-sectional independence - conditions satisfied by our long-panel data structure. The Breitung test employs sequential limit theory, eliminating fixed effects through forward orthogonal transformation and implementing pre-whitening for AR (1) processes. For higher-order autocorrelation, preliminary auxiliary regressions remove serial dependence before residual-based testing. The Hadri LM test extends the KPSS framework to panel data, constructing Lagrange multiplier statistics for stationarity testing.

The LLC and Breitung tests share a common null hypothesis, positing the presence of unit roots in the examined variables, whereas the Hadri LM test adopts the converse null hypothesis of stationarity. Each of the above different types of unit root tests corresponds to three tests under different conditions. The test command with one type of condition cannot reject the assumption that "there is no unit root", that is, the variable is stable in time series.

Cointegration analysis identifies long-term equilibrium relationships among non-stationary yet cointegrated variables. When multiple I (1) processes form stationary linear combinations, they demonstrate stable interactive mechanisms in long-run development. Consider two I (1) random walk processes $\{y_t\}$ and $\{x_t\}$ expressed as:

$$\begin{cases} y_t = \alpha + \beta w_t + \varepsilon_t \\ x_t = \gamma + \delta w_t + u_t \end{cases} \quad (5)$$

The specification incorporates a random walk component $w_t = w_{t-1} + v_t$, where ε_t , u_t , and v_t represent white noise processes. Since both $\{y_t\}$ and $\{x_t\}$ share the common stochastic trend w_t , their linear combination yields a stationary process:

$$\delta y_t - \beta x_t = (\alpha\delta - \beta\gamma) + (\delta\varepsilon_t - \beta u_t) \quad (6)$$

In this scenario, $\{y_t\}$ and $\{x_t\}$ exhibit cointegration. To validate this long-term equilibrium relationship, we employ both Pedroni and Westerlund cointegration tests. The Pedroni test enhances robustness through three model specifications (trend-included with cross-sectional dependence, cross-sectional dependence-only, and intercept-included with cross-sectional dependence), testing the null hypothesis of no cointegration. The Westerlund test further distinguishes between weak cointegration (existing in "some" cross-sections) and strong cointegration (present across "all" cross-sections) as alternative hypotheses, employing multiple specifications (cross-sectional dependence-only, and intercept-included with cross-sectional dependence) for comprehensive assessment. If the results of most of the cointegration test methods show that there is a cointegration relationship, it means that there is a great confidence that the variables in the panel data have a long-term stable relationship.

4.3.2. Spatial Correlation Test

The foundation of spatial econometric analysis lies in verifying the existence of spatial dependence, which serves as the critical prerequisite for adopting spatial models. Spatial autocorrelation captures systematic association patterns among spatial correlation regions in specific variables, where spatial clustering of similar values (high-high or low-low) indicates positive correlation, while space-related dissimilar values (high-low) suggest negative correlation. Random distribution patterns imply the absence of spatial association. This study employs global Moran's I, Geary's C, and Getis & Ord's G tests to determine whether spatial spillover effects exist in agricultural R&D investments.

(1) Moran's I

The global Moran's I index represents a widely adopted measure of spatial autocorrelation in empirical research. Its mathematical formulation is given by:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (7)$$

where x denotes the variable under examination, $S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$ represents the sample variance, w_{ij} corresponds to the (i, j) element of the spatial weight matrix capturing interregional spatial relationships, and $\sum_{i=1}^n \sum_{j=1}^n w_{ij}$ indicates the summation of all spatial weights. The statistic ranges between -1 and 1, with statistically significant values in $(0,1]$ indicating positive spatial autocorrelation, significant values in $[-1,0)$ reflecting negative spatial dependence, and a value of 0 suggesting the absence of spatial association.

(2) Geary's C

The Geary's C statistic is computed as follows:

$$C = \frac{(n-1) \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - x_j)^2}{2 \left(\sum_{i=1}^n \sum_{j=1}^n w_{ij} \right) \left[\sum_{i=1}^n (x_i - \bar{x})^2 \right]} \quad (8)$$

where all variable definitions remain consistent with those in Moran's I. The statistic ranges between 0 and 2, with statistically significant values in $(0,1)$ indicating positive spatial autocorrelation, values significantly greater than 1 demonstrating negative spatial dependence, and a value of 1 representing spatial randomness. Compared to Moran's I, Geary's C exhibits greater sensitivity to local spatial variations, enabling more precise detection of subtle spatial dependence patterns.

(3) Getis & Ord's G

The Getis & Ord G index addresses key limitations of conventional spatial autocorrelation measures by precisely identifying specific clustering patterns. This method quantitatively analyzes spatial distribution patterns of high-value clusters (hot spots) and low-value clusters (cold spots), effectively revealing regional heterogeneity characteristics.

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} x_i x_j}{\sum_{i=1}^n \sum_{j \neq i}^n x_i x_j} \quad (9)$$

The standardized G statistic follows an asymptotic normal distribution, where $Z(G) > 1.96$ indicates statistically significant hot spot clustering, while $Z(G) < -1.96$ denotes significant cold spot clustering.

$$G^* \equiv \frac{G - E(G)}{\sqrt{Var(G)}} \xrightarrow{d} N(0,1) \quad (10)$$

4.3.3. Spatial Econometric Models

Studies examining the impact of per capita agricultural R&D investment on ATRP may yield biased estimates if they neglect spatial dependence and focus solely on local research inputs and farmer characteristics. To address this limitation, spatial econometric methods must be employed to systematically analyze the spatial spillover effects of research investments. As an interdisciplinary approach, spatial econometrics integrates geographical thinking with statistical methods, utilizing spatial weight matrices to quantify regional interconnections, thereby overcoming traditional econometrics' restrictive assumption of spatial independence. For model specification, static analyses primarily employ spatial lag models (SAR), spatial error models (SEM), and spatial Durbin models (SDM), while dynamic analyses focus on advanced spatial dynamic Durbin models and their derivatives.

The most general model specification takes the following form:

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \phi w y_{it} + \eta w y_{i,t-1} + \beta_1 x_{it} + w \beta_2 x_{it} + \beta_3 x_{i,t-1} + w \beta_4 x_{i,t-1} + v_{it} \\ v_{it} = \rho v_{i,t-1} + \lambda w v_{it} + \mu + \xi_t \iota_N + \varepsilon_t \\ \mu = \kappa w \mu + \xi \end{cases} \quad (11)$$

Where y denotes the dependent variable and x represents independent variables, with subscripts i and t indicating economic units and time periods respectively (where $t-1$ signifies one-period lags). Spatial lag terms are constructed through the product of weight matrix w and corresponding variables. The error term v incorporates both serial correlation (coefficient ρ) and spatial dependence (coefficient λ). The model includes μ as spatial fixed effects to control for time-invariant regional heterogeneity - their omission would lead to cross-sectional bias (Baltagi, 2005). Temporal fixed effects ξ_t with corresponding control variables ι_N address time-varying factors, preventing potential time-series bias.

These effects can be specified as either fixed or random. When accounting for spatial autocorrelation, the spatial autoregressive coefficient κ is additionally incorporated into μ .

(1) Static Spatial Econometric Model

The static spatial econometric model represents a specialized case of Equation (11), where $\beta_3=\beta_4=0$, $\tau=\eta=0$, and $\rho=\mu=\xi=0$.

$$\begin{cases} y_{it} = \phi w y_{it} + \beta_1 x_{it} + w \beta_2 x_{it} + v_{it} \\ v_{it} = \lambda w v_{it} + \varepsilon_t \end{cases} \quad (12)$$

This specification yields the general nesting spatial (GNS) model, which incorporates all potential interaction effects through its spatial autoregressive and spatial autocorrelation coefficients. Theoretical and applied research exhibit distinct preferences regarding interaction effects: while spatial econometric theory primarily focuses on the SAR (Eq. 13.03), SEM (Eq. 13.04), and their combined form SAC (Eq. 13.01), empirical applications demonstrate stronger preference for the SDM (Eq. 13.02) due to its comprehensive specification.

$$\begin{cases} y_{it} = \phi w y_{it} + \beta_1 x_{it} + v_{it}; v_{it} = \lambda w v_{it} + \varepsilon_t; \beta_2 = 0 \end{cases} \quad (13.01)$$

$$\begin{cases} y_{it} = \phi w y_{it} + \beta_1 x_{it} + w \beta_2 x_{it} + \varepsilon_t; \lambda = 0 \end{cases} \quad (13.02)$$

$$\begin{cases} y_{it} = \phi w y_{it} + \beta_1 x_{it} + \varepsilon_t; \beta_2 = \lambda = 0 \end{cases} \quad (13.03)$$

$$\begin{cases} y_{it} = \beta_1 x_{it} + v_{it}; v_{it} = \lambda w v_{it} + \varepsilon_t; \beta_2 = \phi = 0 \end{cases} \quad (13.04)$$

The selection of an appropriate spatial econometric model requires complementary diagnostic procedures beyond the spatial correlation tests discussed in Section 4.3.2. Specifically, spatial effects tests must be conducted to determine the optimal model specification. The Hausman test is subsequently employed to determine the appropriate specification between fixed and random effects for the identified spatial model.

(2) Dynamic Spatial Econometric Model

Dynamic spatial econometric models represent a cutting-edge research frontier with ongoing theoretical developments. While Equation (11) presents an idealized specification incorporating all potential variables and effects, empirical applications typically adopt more parsimonious formulations due to theoretical and practical considerations. As Elhorst's (2014) comprehensive review notes, the necessity for further extensions in this direction remains debatable. Currently, the dynamic spatial Durbin model (DSDM) has emerged as the predominant framework, manifesting in five primary specifications:

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \phi w y_{it} + \eta w y_{i,t-1} + \beta_1 x_{it} + w \beta_2 x_{it}; \beta_3 = \beta_4 = \rho = \lambda = \xi_t \iota_N = \xi = \mu \end{cases} \quad (14.01)$$

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \phi w y_{it} + \eta w y_{i,t-1} + \beta_1 x_{it}; \beta_2 = \beta_3 = \beta_4 = \rho = \lambda = \xi_t \iota_N = \xi = \mu \end{cases} \quad (14.02)$$

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \eta w y_{i,t-1} + \beta_1 x_{it} + w \beta_2 x_{it}; \phi = \beta_1 = \beta_2 = \rho = \lambda = \xi_t \iota_N = \xi = \mu \end{cases} \quad (14.03)$$

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \phi w y_{it} + \eta w y_{i,t-1} + \beta_1 x_{it} + w \beta_2 x_{it}; \\ \beta_3 = \beta_4 = \rho = \lambda = \xi_t \iota_N = \xi = \mu \text{ \& Impose Restrictions on } \eta \end{cases} \quad (14.04)$$

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \phi w y_{it} + \beta_1 x_{it} + w \beta_2 x_{it}; \eta = \beta_3 = \beta_4 = \rho = \lambda = \xi_t \iota_N = \xi = \mu \end{cases} \quad (14.05)$$

As Elhorst's (2014) review notes indicate that Equation (14.01) extends the static SDM to dynamic specifications, while Equations (14.02) -(14.05) represent its derivatives, all demonstrating explanatory power in regional economic growth and convergence studies. Our empirical analysis initially employed Equation (14.01) as the baseline model, but diagnostic tests indicated model degeneration, leading to the following simplified specification:

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \beta_1 x_{it} + w \beta_2 x_{it} + \mu \\ \mu = \kappa w \mu + \xi \end{cases} \quad (15)$$

5. Empirical Results

5.1 Panel Pre-Test Analysis

5.1.1. Unit Root Tests

Table 1 presents the results from three unit root tests for key variables. The analysis reveals that ATFP and per capita

R&D investment in RDI appear stationary under both LLC and Breitung tests, though Hadri LM yields contradictory results. EDU levels show stationarity only in the Breitung test. Following econometric conventions, stationarity is preliminarily confirmed if supported by any single test, suggesting that ATFP, RDI investment, and EDU can be treated as stationary series. However, the lack of consistent results across tests weakens the robustness of this conclusion. Notably, HE and LBDE fail to demonstrate stationarity in any test.

Table 1. Unit Root Test Results

Conditions/ Variables	ATFP			RDI			HE			LBDE			EDU		
Test	LLC	Breitung	Hadri LM	LLC	Breitung	Hadri LM	LLC	Breitung	Hadri LM	LLC	Breitung	Hadri LM	LLC	Breitung	Hadri LM
Noconstant	-1.4357	-1.1013	-	-2.6659	-2.7096	-	-7.7974	-7.6745	-	-6.4755	-7.9329	-	-4.5562	-4.2241	-
& Demean	*			***	***		***	***		***	***		***	***	
Demean	-0.4841	-1.7624	57.9401	0.7618	-0.2580	66.2106	-4.4763	-2.1677	37.8047	5.0792	-8.6873	16.7155	-2.6739	-0.9050	61.8909
	**		***			***	***	**	***	***	***	***	***		***
Trend &	-2.5201	-2.0995	33.8385	-2.7969	-2.8630	33.9688	-5.8957	-4.9714	21.5732	-4.9517	-8.0414	12.0945	-2.3200	-6.1180	18.5227
Demean	***	**	***	***	***	***	***	***	***	***	***	***	**	***	***
Trend &			23.4804			23.7653			31.5174			17.1632			19.1184
Robust	-	-	***	-	-	***	-	-	***	-	-	***	-	-	***
Whether or not stationary on a time series	Yes	Yes	No	Yes	Yes	No	No	No	No	No	No	No	No	Yes	No

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

5.1.2. Cointegration Test

As shown in Table 2, the Pedroni test provides partial evidence for cointegration, while the Westerlund test completely rejects it. This conflicting outcome implies that while long-term equilibrium relationships between regional agricultural R&D and ATFP may exist in China, the statistical evidence remains inconclusive.

Table 2. Cointegration Test Results

Conditions	Pedroni Test			Westerlund Test		
	Modified	Phillips-Perron	Augmented	Conditions	Variance ratio	
	Phillips-Perron	t	Dickey-Fuller			
	t	t	t			
Trend & Demean	4.8539 ***	-1.1647	-0.8868	The alternative hypothesis:	Demean	-0.5076
Demean	3.2497 ***	-2.2822 **	-1.8887 **	Some cross-sections with cointegration	Trend & Demean	0.8742
Noconstant & Demean	2.7794 ***	-2.8767 ***	-3.1321 ***	The alternative hypothesis: All cross-sections with cointegration	Demean	-0.6880
					Trend & Demean	-0.3654

Whether or not cointegration
presented

Yes

No

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

The time series analysis yields mixed results: ATFP, RDI, and EDU show partial but inconsistent evidence of stationarity, while HE and LBDE exhibit non-stationarity across all tests. Similarly, cointegration tests produce unstable outcomes. Nevertheless, the partial stationarity of ATFP and RDI provides a minimal temporal basis for subsequent dynamic spatial econometric analysis.

5.2. Static Spatial Pre-Test Analysis

Prior to conducting static spatial regression, we implement a two-stage pre-test procedure. The initial spatial autocorrelation test determines the presence of spatial dependence, followed by a spatial effects test to identify the appropriate model specification.

Table 3 presents global spatial autocorrelation results for all variables under both spatial weight matrices.

Table 3. Global Spatial Autocorrelation Test Results

	Moran's I		Geary's c		Getis& Ord's G	
	AM	GM	AM	GM	AM	GM
ATFP	0.096***	0.101***	0.818***	0.749***	0.154***	0.340***
RDI	0.047***	0.059***	0.963**	0.907***	0.146***	0.320***
HE	0.054***	0.032***	0.916***	0.966	0.15	0.338***
LBDE	0.035***	0.013***	0.948***	0.993	0.15	0.335***
EDU	0.145***	0.049***	0.752***	0.878***	0.169***	0.374***

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

The comprehensive tests reveal strong spatial dependence for ATFP, RDI investment, and EDU, as evidenced by consistent significance across all three tests. Following econometric standards, variables passing all tests demonstrate "strong spatial correlation," while those with partial significance (HE and LBDE) exhibit "weak spatial correlation."

Notably, the AM and the GM produce highly consistent results, with divergences only appearing in Geary's C and Getis-Ord's G tests for HE and LBDE. This finding fails to support Hypothesis 4 (superiority of agricultural geography matrix) at the first analytical dimension.

The spatial effects test serves a dual purpose: identifying spatial heterogeneity (structural differences in data generation across geographic units) and selecting optimal spatial econometric models. Table 4 presents the test results under both spatial weight matrices examined in this study.

Table 4. Spatial Effects Test Results

	AM	GM		AM	GM
Spatial error:			Spatial lag:		
Moran's I	0.678	0.928			
Lagrange multiplier	639.048***	1112.980***	Lagrange multiplier	31.250***	7.524***
Robust Lagrange multiplier	645.812***	1115.266***	Robust Lagrange multiplier	38.015***	9.810***

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

The statistical significance of both error and autocorrelation measures under both spatial weight matrix specifications (with two out of three error statistics and both autocorrelation statistics being significant) confirms the stable spatial dependence among study variables in spatial correlation regions. These findings empirically justify the

application of both SEM and SAR models. Consequently, this study adopts the SDM as the primary analytical framework, given its capacity to simultaneously capture both the error and lag spatial effects.

The test results demonstrate solid econometric foundations for employing static spatial regression models in this study. Importantly, both spatial weight matrix specifications support the appropriateness of SDM, providing a robust basis for model selection. Subsequent analysis will employ Hausman tests to determine the optimal specification between fixed and random effects models, ensuring the validity of estimation results.

Table 5. Hausman Test for Static Spatial Model

	AM		GM			AM		GM	
	RE	FE	RE	FE		RE	FE	RE	FE
R-sq:					Variance	Coef.	Coef.	Coef.	Coef.
within	0.9316	0.9323	0.9310	0.9316	ln(RDI)	0.6574	0.6300	0.6389	0.6175
						***	***	***	***
between	0.8326	0.6484	0.8408	0.6646	ln(HE)	0.0077*	0.0112*	0.0063*	0.0102*
overall	0.8090	0.6954	0.8068	0.6984	ln(LBDE)	0.0304	0.0284	0.0239	0.0207
						**	**	*	*
					ln(EDU)	0.0840	0.0205	0.0932***	0.0350
						***			*
					con	0.3866		0.5092	
						***		**	
					Variance Wx				
					ln(RDI)	-0.2753	-0.2525	-0.2866	-0.2547
						***	***	***	***
Test:	Prob>chi2= 0.9464		Prob>chi2= 0.9464		ln(HE)	-0.0522	-0.0537	-0.0404	-0.0458
						***	***	***	***
Ho: difference in	-25.09		-29.760		ln(LBDE)	-0.0082	-0.0071	0.0001	0.0028
coefficients not					ln(EDU)	-0.0110	0.0493	-0.0513	0.0246
systematic					rho	0.3482	0.3543	0.3616	0.3663
						***	***	***	***

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

Table 5 presents the regression results of both random and fixed effects SDM under two spatial weight matrix specifications, along with Hausman test outcomes. The results demonstrate the superiority of random effects models across most goodness-of-fit measures and variable significance levels. Particularly, the negative Hausman statistic provides strong econometric evidence favoring random effects specification.

Comparative analysis reveals minimal differences between AM and GM performance. While AM shows marginally better overall fit, the elasticity coefficients differ by merely 0.01 magnitude with nearly identical significance levels - in fact, some variables exhibit slightly higher significance under AM. This systematic comparison fails to support Hypothesis 4 in the latter two analytical dimensions.

5.3. Dynamic Spatial Pre-Test Analysis

This study conducts two essential diagnostic tests for dynamic spatial modeling: spatial autocorrelation and heteroskedasticity tests. The spatial autocorrelation test serves dual purposes - first verifying the existence of spatial dependence in the dataset, then guiding the selection of appropriate dynamic spatial model specifications. The spatial heteroskedasticity test, when significant, indicates the necessity of incorporating spatial lag terms in modeling framework.

Table 6 presents key diagnostic results for dynamic spatial modeling. The spatial autocorrelation tests reveal significant spatial dependence in error terms (Group01), spatial lags (Group02), and their combined effects (Group03), strongly justifying the use of dynamic spatial regression. These findings particularly support adopting the DSDM, given its capacity to capture complex spatial interactions. Notably, both AM and GM yield virtually identical test results, especially in terms of spatial autocorrelation significance levels. This consistency fails to support the hypothesized superiority of GM (Hypothesis 4) in dynamic regression analysis.

Table 6. Dynamic Spatial Panel Autocorrelation Test Results

Group01 Error			Group02 Spatial Lagged Dependent Variable		
Ho: Error has No Spatial Autocorrelation			Ho: Spatial Lagged Dependent Variable has No Spatial Autocorrelation		
Ha: Error has	Spatial Autocorrelation		Ha: Spatial Lagged Dependent Variable has	Spatial Autocorrelation	
	AM	GM		AM	GM
GLOBAL Moran I	0.9222***	0.8382***	LM Lag (Anselin)	611.9119***	698.5351***
GLOBAL Geary C	0.0998***	0.1699***	LM Lag (Robust)	6603.0625***	4872.8633***
GLOBAL Getis-Ords	-4.2836***	-8.5986***	Group03 General Spatial Autocorrelation		
Moran I Error	8.5552***	5.6855***	Ho: No General Spatial Autocorrelation		
LM Error (Burridge)	1434.1466***	2616.7688***	Ha: General Spatial Autocorrelation		
LM Error (Robust)	7425.2972***	6791.0970***	LM (LMErr+LMLag_R)	8037.2091***	7489.6322***
			LM (LMLag+LMErr_R)	8037.2091***	7489.6322***

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

Table 7 presents the LM heteroskedasticity test results under both spatial weight matrix specifications. The analysis reveals limited evidence of variable-specific spatial heteroskedasticity: under the AM, only HE, EDU (non-robust), and spatially lagged RDI (at 10% significance level) exhibit such characteristics, while the GM shows similar patterns for RDI (non-robust), HE, and EDU (non-robust). However, comprehensive global tests - including Hall-Pagan LM, Harvey LM, Wald, White, and Cook-Weisberg LM tests - consistently demonstrate significant spatial heteroskedasticity in both matrix specifications (full results not shown for brevity). This finding provides strong econometric justification for incorporating spatial lag terms to ensure the validity of parameter estimates.

Table 7. Single Variable Heteroscedasticity Tests Results

Variables	AM		GM	
	Cook-Weisberg LM(E2/Sig2)	King LM	Cook-Weisberg LM(E2/Sig2)	King LM
RDI	2.0886	2.6956	2.1639	2.8335***
HE	8.3815***	7.0053***	8.2274***	6.8799***
LBDE	2.0925	0.5783	1.5723	0.3514
EDU	3.7915*	1.5511	3.4041*	1.2084
w1x_RDI	3.2149*	2.7538*	0.8536	1.2052
w1x_HE	0.5366	0.4095	0.7274	0.7256
w1x_LBDE	0.0002	0.0976	0.0522	0.0554
w1x_EDU	2.0638	1.5348	0.1853	0.1356

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

Having established the dynamic spatial Durbin model as our analytical framework, we proceed to determine the appropriate specification between fixed effects (FE) and random effects (RE) through comparative analysis. Table 8

presents the regression results for both specifications under alternative spatial weight matrices.

Table 8. FE and RE Comparative Analysis for DSDM

	AM		GM			AM		GM	
	RE	FE	RE	FE		RE	FE	RE	FE
Wald Test	1912.4595 ***	1787.9718 ***	1886.7970 ***	1814.9525 ***	Variance	Coef.	Coef.	Coef.	Coef.
F-Test	212.4955 ***	198.6635 ***	209.6440 ***	201.6614 ***	ATFP Lag	0.9025 ***	0.8974 ***	0.8930 ***	0.9108 ***
R2	0.7224	0.7087	0.7197	0.7118	RDI	0.096*	0.124**	0.090*	0.109*
R2 Adj	0.7194	0.7055	0.7166	0.7086	HE	0.007*	0.027*	0.009*	0.018*
Raw Moments	0.9855	0.9866	0.9858	0.9856	LBDE	0.7169	0.6871	0.7122	0.6911
R2						***	***	***	***
Raw Moments	0.9854	0.9864	0.9857	0.9855	EDU	0.1313	0.0749	0.1337	0.0786
R2 Adj						***	***	***	***
Log Likelihood	-194.7898	-166.8010	-186.8698	-192.3074	Variance Wx				
R2h	0.9585	0.8919	0.9558	0.9180	RDI	0.078 ***	0.071 ***	0.036 ***	0.034 ***
R2h Adj	0.9580	0.8907	0.9554	0.9171	HE	-0.068 ***	-0.030	-0.037 ***	-0.022 *
F-Test	1884.8300 ***	673.8100 ***	1767.4500 ***	913.8500 ***	LBDE	-0.0037	-0.0185 **	-0.0020	-0.0057
					EDU	0.0097 ***	-0.0091	0.0023	-0.0012

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

The model comparison reveals several findings. First, the RE demonstrate superior performance across multiple goodness-of-fit measures and variable significance levels. Although we initially adopted the specification in Equation (14.01), empirical results indicated model degeneration, leading to the simplified form presented in Equation (15) of Chapter 4. Second, the AM and the GM show minimal differences in model performance. While AM exhibits marginally better overall fit, the elasticity coefficients differ by only 0.01 magnitude with identical significance levels. These results collectively reject Hypothesis 4 regarding the superiority of GM in the latter two analytical dimensions.

The final spatial panel model selection criteria demonstrate the feasibility of random effects DSDM specifications under both matrix configurations. Comparative results reveal mixed evidence: GM performs better under LLF criteria, while AM shows advantages in AIC (including log-AIC) and SC (including log-SC) measures. This pattern further confirms the functional equivalence of both spatial weight matrix specifications.

Table 9. Spatial Panel Model Selection Diagnostic Criteria

Test	AM	GM	Test	AM	GM
LLF	-194.7898	-186.8698	FPE	0.1017	0.0995
AIC	0.1021	0.0999	HQ	0.1051	0.1028
Log AIC	-2.2820	-2.3033	Rice	0.1021	0.1000
SC	0.1100	0.1076	Shibata	0.1020	0.0999
Log SC	-2.2076	-2.2289	GCV	0.1021	0.1000

Source: Authors own work

Notably, the dynamic spatial models exhibit significantly inferior empirical performance compared to their static counterparts, as evidenced by both goodness-of-fit measures and variable significance levels - a finding consistent with existing literature. This reveals an important specification challenge in dynamic spatial modeling: while theoretically comprehensive specifications like Equation (11) satisfy methodological rigor, they often encounter insignificant coefficients or model degeneration in practice. These results suggest researchers should strike a careful balance between theoretical completeness and empirical feasibility in dynamic spatial analysis, emphasizing prudent variable selection and model optimization as fundamental principles.

5.4. Static Spatial Effect Results

The static spatial random effects Durbin model analysis reveals several key findings regarding the spatial spillover effects of per capita agricultural R&D investment under both AM and GM. Effect decomposition distinguishes between: (1) direct effects measuring local ATFP impacts, and (2) indirect effects capturing spatial spillovers to spatially related regions.

Table 10. Static Spatial Effect Results

	LR Direct Effect		LR Indirect Effect		LR Total Effect	
	AM	GM	AM	GM	AM	GM
RDI	0.6552***	0.6370***	-0.0676**	-0.0807*	0.5877***	0.5563***
HE	0.0026*	0.0035*	-0.0709***	-0.0573***	-0.0683***	-0.0538***
LBDE	0.0319***	0.0257**	0.0018	0.0111	0.0336**	0.0369**
EDU	0.0855***	0.0916***	0.0269	-0.0234	0.1124***	0.0682

Note: ***, **, * represent significance at the 1% level, 5% level, and 10% levels.

Source: Authors own work

Direct effects demonstrate substantial institutional heterogeneity. RDI exhibit the strongest local productivity enhancement, with 1% investment increases boosting ATFP by 63.70% (GM) and 65.52% (AM) - significantly outperforming other factors. In contrast, HE investments show weak, statistically weak significant local effects (0.26% in AM and 0.35% in GM). EDU and LBDE emerge as the second and third most influential factors respectively.

Spatial spillovers display consistent negative patterns: spatially related regions' RDI increases reduce local ATFP by 6.76%(AM)-8.07%(GM), with HE showing similar negative effects (5.73% in GM and 7.09% in AM). This "resource siphoning" phenomenon reflects excessive R&D concentration in municipalities, agricultural hubs, and developed regions (Table 11), indicating structural imbalances in research resource allocation.

Table 11. Average per Capita Investment Spillovers in Provinces with Research Spillovers

Province	BJ	TJ	HB	LN	HLJ	SH	JS	ZJ	AH	HN	HuB	HuN	GD	HaiN	CQ	SC	SnX
Static Aver RDI impact on the relative province (AM) (1 thousand Yuan/ Researcher)	12.95	8.95	8.50	8.49		13.66	11.05	8.96	8.42		9.16		9.92	8.60		11.89	10.28
Static Aver HE impact on the relative province (AM) (1 thousand Yuan/ FTE per year)	8.20	8.60		4.77	5.04	6.53	7.22	6.79	5.45	4.89	5.72	5.38	5.88		5.56	5.59	5.84
Static Aver RDI impact on the relative province (GM) (1 thousand Yuan/ Researcher)	15.46	10.68	10.15	10.14		16.30	13.18	10.69	10.05		10.93		11.84	10.27		14.19	12.27
Static Aver HE impact on the relative province (GM) (1 thousand Yuan/ FTE per year)	6.63	6.96		3.86	4.07	5.28	5.84	5.49	4.41	3.95	4.63	4.35	4.76		4.49	4.52	4.72

Source: Authors own work

Notably, RDI demonstrates 1.82 times higher per capita investment than HE but generates 182(in GM)-252(in AM) times greater direct effects, supporting Hypothesis 1 regarding institutional efficiency differences. However, both institutions exhibit negative spatial externalities (RDI's being 1.43(in AM)-2.11(in GM) times stronger than HE's), rejecting Hypothesis 2's expectation of positive spillovers. The distinct "weak local effects but strong spatial drag" pattern of HE, coupled with RDI's pronounced negative spillovers under GM, highlights significant institutional heterogeneity in spatial impacts.

5.5. Dynamic Spatial Effect Results

The dynamic spatial random effects Durbin model analysis reveals several key temporal patterns in agricultural R&D investment impacts under alternative spatial weight matrix specifications. Compared to static model estimates, incorporating temporal dynamics leads to substantial attenuation in both short-term direct and indirect effect magnitudes, with uniformly reduced elasticity coefficients across variables. These results demonstrate pronounced time-lag characteristics in research spillovers, where spatial effects weaken considerably when accounting for dynamic adjustments. Table 12 presents the detailed temporal evolution of these spatiotemporal effects.

Table 12. Dynamic Spatial Effect Results

	Short Term				Long Term			
	LR Direct Effect		LR Indirect Effect		LR Direct Effect		LR Indirect Effect	
	AM	GM	AM	GM	AM	GM	AM	GM
RDI	0.0148	0.0148	0.0148	0.0267	0.0167	0.0197	-0.0121	-0.0267
HE	-0.0100	-0.0120	-0.0105	-0.0233	0.0414	0.0465	0.0105	0.0233
LBDE	0.2257	0.2231	-0.0057	-0.0127	-0.1943	-0.1886	0.0057	0.0127
EDU	0.0569	0.0507	0.0150	0.0332	-0.0254	-0.0162	-0.0150	-0.0332

Source: Authors own work

5.5.1. Short-term Dynamic Spatial Effect Results

Short-term dynamic analysis reveals distinct patterns in direct effects. LBDE demonstrates the strongest immediate impact, with a 1% increase boosting TFP by 22.31% (AM) and 22.57% (GM), establishing it as the primary short-term growth driver. Farmer education ranks second, while RDI investments show limited short-term effects across both matrices. Notably, HE exhibits a unique "resource crowding-out" effect, reducing local TFP by 1%(AM) and 1.2%(GM).

Spatial spillovers present more nuanced short-term dynamics. Spatial related regions' RDI increases enhance local ATFP by 1.48% (AM) and 2.67% (GM), whereas HE maintains negative spillovers (-1.05%(AM) and 2.33%(GM)). Farmer education emerges as the most significant positive spatial externality. These findings fully support Hypothesis 3, confirming that RDI's applied research generates immediate benefits while HE's basic research produces initial negative impacts due to resource displacement effects.

5.5.2. Long-term Dynamic Spatial Effect Results

The long-term dynamic analysis reveals distinctive temporal patterns in research impacts. HE investments demonstrate significant cumulative effects, with 1% increases elevating TFP by 4.14% (AM) and 4.65% (GM) - surpassing RDI's long-term contributions (1.67%(AM) and 1.97% (GM)). This reversal from short-term negative to long-term positive effects underscores the delayed returns characteristic of basic research investments, while other factors consistently show negative long-term impacts.

Spatial spillovers exhibit complex evolutionary patterns: RDI transitions from short-term positive to long-term negative effects (-1.21%(AM) to 2.67%(GM)), suggesting potential resource allocation inefficiencies, whereas HE shows an opposite transformation (1.05%(AM)-2.33%(GM)). Remarkably, despite RDI's 1.82 times higher per capita investment than HE, its long-term direct effects reach only 40%(AM) and 42%(GM) of HE's impacts - this substantial

input-output disparity rejects Hypothesis 1 regarding long-term research effectiveness.

These findings collectively demonstrate fundamental temporal differences: HE's basic research yields delayed but sustained benefits, while RDI's applied research follows a "short-term effective, long-term diminishing" trajectory, clearly contradicting Hypothesis 2's assumptions about long-term spatial spillovers. The results highlight the critical importance of temporal dimensions in evaluating research effectiveness and spatial externalities.

6. Conclusion and discussion

Based on the hypotheses set forth in this study, the direct effects align with theoretical and common-sense expectations. However, in terms of spillover effects, results contrary to theory and common understanding emerged, posing a practical issue uncovered during empirical analysis. While acknowledging that dynamic spatial models are still evolving, this should not serve as a justification for dismissing their conclusions.

Regarding static spatial model findings, both institutions were found to exhibit negative spatial spillover effects. Partly attributed to transfer payments, which, upon comprehensive comparison, accounted for only approximately 6-7% of the scientific research resources in research-intensive provinces. Excluding the impact on the home province, the remainder potentially represents wastage in per capita R&D investment. Furthermore, the static model reveals that RDI demonstrates a significantly higher direct effect compared to HE. While highlighting RDI's efficiency, it also underscores HE's relatively lower research efficiency from a static perspective. In terms of spillover effects, under AM relations, HE exerts a more severe crowding-out effect on ATFP, whereas under GM relations, RDI's impact is more pronounced. From a dynamic standpoint, in the short term, RDI effectively offsets the disparity of HE's negative direct effect, preventing the combined direct effects of both research entities from being negative. In the long term, HE demonstrates stronger research-driving capabilities, with its long-term direct effect is 2.4 times (AM) and 2.36 times (GM) that of RDI, indicating HE's effective long-term research promotion within its province. However, the spillover effect scenario is less optimistic, as HE fails to effectively offset the crowding-out effect on ATFP in spatially correlated provinces over the long term, resulting in a negative total long-term spillover effect for both research entities.

Ultimately, the results indicate: at the static level, while RDI and HE exhibit strong direct effects, they fail to demonstrate spatial externalities of knowledge. This concentration of research resources instead exerts a crowding-out effect on ATFP. Dynamically, Higher Education shows an initial inhibitory followed by a promoting effect on ATFP, whereas RDI exhibits strong negative externalities in the long term.

A systematic comparison between recent literature and this study's findings reveals both notable disparities and shared characteristics in the spatial effects of R&D investment on TFP. Building on Nadiri's (1993) early estimate that R&D investment exhibits an output elasticity range of 0.1–0.3 for TFP, Dai et al. (2022) reported impact coefficients of internal R&D capital stock on firm-level TFP between 0.094 and 0.123. Scherngell et al. (2013), examining the impact of intellectual capital on manufacturing TFP across Chinese regions in the early 21st century, reported direct and indirect effects of 0.025 and 0.031, respectively. The studies by Liu & Zhang (2013) on regional spillover effects of R&D activities in China's high-tech industries and Zhao & Hu (2012) on spatial spillover effects of knowledge output across Chinese provinces offer strong comparability to this study in terms of temporal scope and perspective. Although neither study calculated direct and indirect effects, they found elasticity coefficients for internal R&D expenditure ranging from -0.112 to 0.317 under various scenarios (compared to 0.006-0.657 in this study), while those including spatial lag terms ranged from -0.184 to 0.25 (compared to -0.2866 to 0.078 in this study). These results partially overlap with the direct effect range (0.0026–0.6552) observed in this study's static model, though our static analysis demonstrates substantially higher direct effect values for R&D investment (direct effect of RDI=0.6552). While dynamic direct effects show greater alignment with earlier studies, this study uniquely identifies potential negative direct effects, suggesting spatial crowding-out effects of R&D investment under industry-specific and methodological heterogeneity.

Regarding dynamic effects, Fischer et al. (2009) employed a spatial error model across 203 NUTS-2 regions and

found a 0.12 elasticity of knowledge spillovers on regional TFP. Though directionally consistent with this study's long-term dynamic effect range (0.0167–0.0465), the magnitude discrepancy likely stems from differences in model specification and industrial contexts.

Comparative analysis with international studies reveals important contextual variations. Tientao et al. (2014) demonstrated positive direct (0.006–0.012) and indirect (0.019–0.065) effects of R&D on cross-country TFP spillovers, showing partial alignment with our findings. However, Herzer's (2022) research on developing countries reports substantially higher domestic R&D elasticities (0.243–0.310) than our estimates, potentially reflecting two key factors: our finer institutional disaggregation and China's unique research allocation patterns that may diminish marginal returns. Particularly noteworthy are the short-term negative effects identified in our dynamic model (direct: -0.012 to 0.0148; indirect: -0.0233 to 0.0267), providing novel evidence that under the influence of policy delays and other factors, the spatial spillover of R&D investment may experience a complex inhibitory-then-stimulatory paths.

Through the comparative analysis of the existing literature and the results of this study, the following findings can be obtained: First, while confirming fundamental theoretical expectations about R&D's spatial direct effects, our results highlight how contextual factors significantly influence outcome estimates. Second, the dynamic spatial analysis uncovers counterintuitive spatiotemporal patterns across research institutions, offering new empirical evidence about their differential innovation efficiencies. The concentrated R&D allocation mode demonstrates particularly strong negative spillovers to spatial correlation regions - most prominently for HE in static models and RDI in long-term dynamic analyses. Third, contrasting with Zhu's (2024) findings on GM superiority in localized studies, our large-sample analysis shows no clear advantage for GM over AM. This scale-dependent result suggests geographical factors dominate in small, heterogeneous areas while traditional adjacency relationships remain more relevant in broader regional contexts - an important methodological consideration for future spatial research design. However, the similarity in findings derived from the two types of spatial correlation matrices, to a certain extent, demonstrates the robustness of the conclusions in this study.

In summary, this study elucidates the differentiated impact mechanisms of R&D investment from diverse entities on ATFP, offering insights for optimizing regional innovation resource allocation. It advocates for tailored support policies aligned with the distinct characteristics of various research institutions, emphasizes the significance of spatial-temporal synergy in R&D investment, and underscores the necessity of enhancing interregional knowledge spillover mechanisms to fully harness the potential of R&D investment in promoting agricultural innovation.

Future research may focus on two key directions to advance this field. First, developing multiscale dynamic spatial models that integrate micro-level firm data with macro-level regional panels would better elucidate the differential mechanisms of research institutions across short-term policy lags and long-term knowledge accumulation effects. Finally, methodological innovations should explore hybrid spatial weight matrices combining geographical adjacency, economic linkages, and agricultural ecological zoning, potentially employing machine learning techniques for adaptive parameter optimization to resolve the GM-AM matrix debate through more universal analytical frameworks.

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