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Spatial Effects of Innovation Efficiency in High-tech Industries Based on DEA-Malmquist Model

Chenyang He*
Department of Finance and Economics, Taiyuan University, Taiyuan 030032, China
**Corresponding Author.*

Abstract:
New productive forces, driven by innovation and characterized by high-tech features, are essential for promoting high-quality economic development. These forces emphasize technological innovation as their core and industrial upgrading as their direction. Based on this premise, this paper combines the upgrading of high-tech industry with scientific and technological innovation, analyzing the innovation efficiency and the spatial effect. The results reveal significant regional disparities in the innovation efficiency across 30 regions in china, with notable differences between the Beijing-Tianjin-Hebei economic region, coastal areas, and other regions. Analysis indicates that the panel Spatial Lag Model provides the best fit. Government support, economic development, and urbanization exert positive spatial effects on innovation efficiency, while technological talent, international openness, and education exhibit negative spatial effects.

Keywords: new productive forces, high-tech industries, innovation efficiency, spatial differences, spatial econometric models.

INTRODUCTION

Under the trend of rapid economic development and rapid scientific and technological progress, high-tech industries hold a significant position in promoting economic growth. A report stressed that china must focus our economic development on the real economy. The emergence of new quality productivity takes scientific and technological innovation as the core and industrial upgrading as the direction, indicating the urgency of combining industrial upgrading and scientific and technological innovation. High-tech industries integrate the development of science and technology, talents, innovation and real economy. Under the general trend of high-quality economic development, we must pay attention to the dual development of science and technology and economy of high-tech industry.

Scholars' research on innovation efficiency mainly revolves around the application of SFA[1] and DEA methods. In 1977, Aiger et al.[2] proposed the SFA model, and in 1978, Charens et al.[3] introduced the DEA model. Since then, many scholars have begun to use SFA and DEA methods to conduct research. In terms of high-tech industry, few scholars have studied its innovation efficiency. Rouven E. haschka and others have conducted relevant research in Europe with the help of Bayesian stochastic frontier method and found that the growing pressure of innovation may cause vicious innovation competition.

For high-tech industries, scholars study the impact of innovation efficiency on economic development relatively more. Cheng et al.[4] applied the three-stage super efficiency SBM model to measure, which showed that the overall trend was on the rise. Du et al.[5] used the spatial stochastic frontier method to calculate, which showed that the digital finance had a significant positive impact on it. Wang et al.[6] applied the three-stage network DEA model to calculate the Yangtze River Delta region, and the results showed that it showed a steady upward trend. Song et al.[7] applied DEA Malmquist model to calculate its regional heterogeneity. Which showed that the efficiency is high in the East and low in the west, and there are great differences between regions. With the help of DEA Malmquist, Zou et al.[8] analyzed the perspective of industry university research cooperation in the Yangtze River economic belt. The results show that the overall innovation efficiency is high. Fan et al.[9] applied DEA Malmquist method to calculate, and the results showed that the overall increase was slight.

From the existing literature, it can be observed that research related to the topic of this article mainly focuses on individual provinces or divides regions for analysis. However, the lack of finer regional divisions results in insufficient reflection of regional differences. This paper divides 30 regions in China (excluding Xizang Autonomous Region) into seven major economic development regions for a more detailed analysis of regional differences. This paper conducts analysis based on a spatial econometric model and supplements relevant literature.

THEORY MODEL

DEA-Malmquist model

The Malmquist productivity exponential model based on the distance function is proposed by Caves[10-11], period t and period t+1 are expressed as Equation (1).

$$M_0{}^{t}(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \quad M_0{}^{t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_t, y_t)} \tag{1}$$

From period t to period t+1 is expressed as Equation (2).

$$M_0(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \times \left(\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)} \right)^{1/2} = EC \times TC \tag{2}$$

In Equation (2), EC is the technical efficiency index, and TC is the technical progress index[12].

Spatial Econometric Models

Elhorst proposed a spatial regression model for panel data[13-14], and the spatial panel lag model (SLM model) is expressed as Equation (3).

$$\begin{aligned} & y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \\ & \varepsilon_{it} \sim N(0, \sigma^2 I_N) \end{aligned} \tag{3}$$

The spatial panel error model (SEM model) is expressed as Equation (4).

$$\begin{cases} y_{it} = x_{it}\beta + \mu_i + u_{it} \\ u_{it} = \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \\ \varepsilon_{it} \sim N(0, \sigma^2 I_N) \end{cases} \tag{4}$$

The spatial panel Durbin model (SDM model) [15] is expressed as Equation (5).

$$\begin{aligned} & y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \delta \sum_{j=1}^{N} w_{ij} x_{jt} + \mu_i + \varepsilon_{it} \\ & \varepsilon_{it} \sim N(0, \sigma^2 I_N) \end{aligned} \tag{5}$$

In Equation (3)-(5), x_{it} represents the value of the independent variable (explanatory variable) for the (i)-th spatial unit at time (t); y_{it} represents the value of the dependent variable (explained variable) for the (i)-th spatial unit at time (t); w_{ij} is the spatial weight matrix, which describes the spatial relationships or adjacency relationships between spatial units; μ_i represents individual fixed effects; ρ is the spatial lag regression coefficient; and λ is the spatial error regression coefficient.

INDICATOR SYSTEM AND DATA SOURCES

This study employs the DEA-Malmquist model to measure the innovation efficiency of high-tech industries[16]. The indicators used in this model include input and output variables, which are selected based on the perspective of innovation production in high-tech industries and synthesized from the findings of previous studies. The indicator system is shown in Table 1.

Table 1. Indicator system for measuring innovation efficiency in high-tech industries

The indicator system	
Input indicators	**output indicators**
Full-time equivalent of R&D personnel	number of new product development projects
internal expenditure on R&D	number of valid invention patents
expenditure on new product development	sales revenue of new products
amount of technology introduction contracts	

In addition to measuring the innovation efficiency of 30 provinces, municipalities, and autonomous regions in China (excluding Xizang Autonomous Region due to data limitations), this study conducts a regional disparity analysis by dividing the regions into seven major economic zones in Table 2. The regional division criteria consider both geographical proximity and the spatial compatibility of economic development.

Table 2. Regional division criteria

Regional division	Northeast China	Liaoning, Jilin, Heilongjiang
	North China	Beijing, Tianjin, Hebei, Inner Mongolia
	Central China	Shanxi, Henan, Hubei, Anhui, Hunan, Jiangxi
	East China	Shanghai, Jiangsu, Zhejiang, Fujian, Shandong
	South China	Guangdong, Guangxi, Hainan
	Northwest China	Xinjiang, Qinghai, Gansu, Ningxia, Shaanxi
	Southwest China	Yunnan, Guizhou, Sichuan, Chongqing

The sample data used in this study cover the period from 2009 to 2021. All data are sourced from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China High-tech Industry Statistical Yearbook. Due to the severe lack of data for Xizang Autonomous Region, it has been excluded from the analysis to ensure the validity of the empirical results. Missing data for other provinces were supplemented using interpolation methods to ensure data completeness.

SPATIAL DISPARITIES

Regional Measurements

The innovation efficiency of high-tech industries in the seven major economic zones is summarized in Figure 1-7.

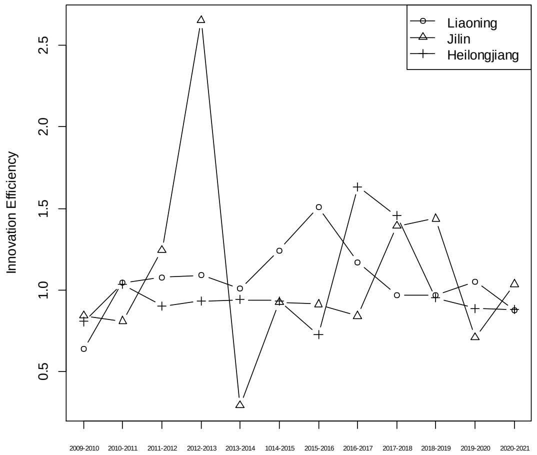

Figure 1. Northeast China

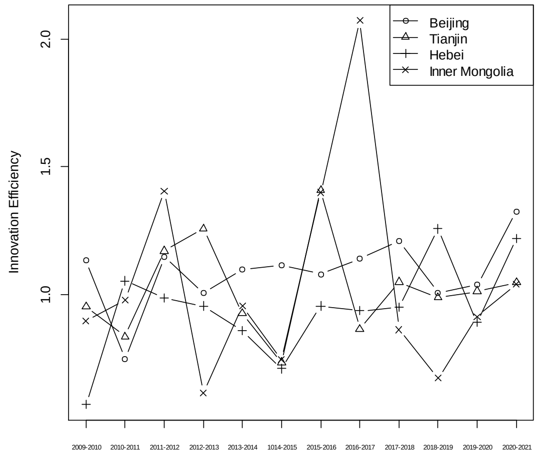

Figure 2. North China

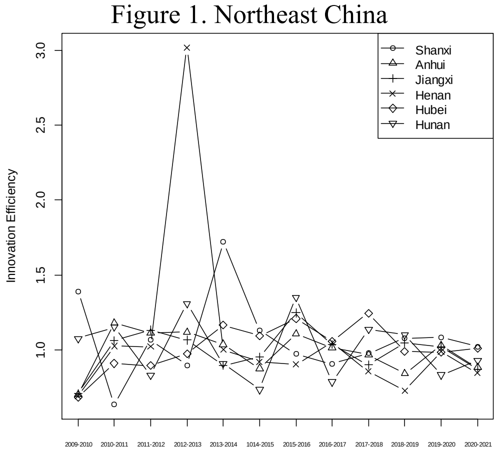

Figure 3. Central China

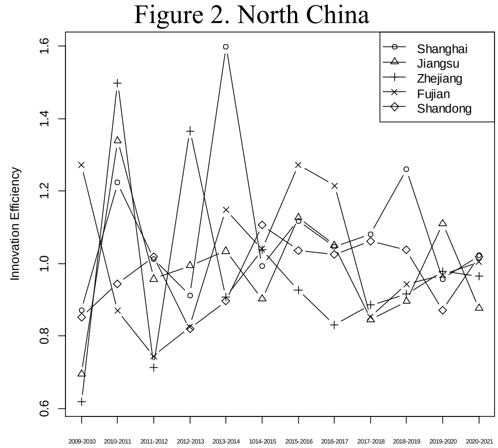

Figure 4. East China

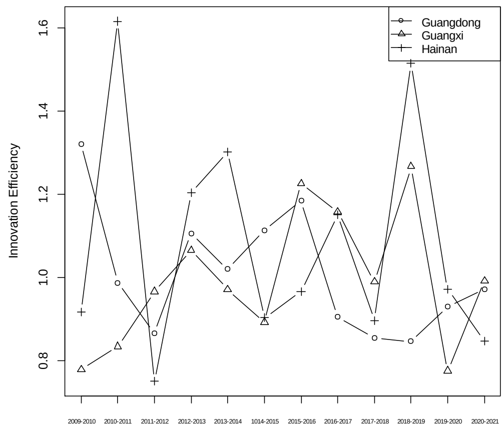

Figure 5. South China

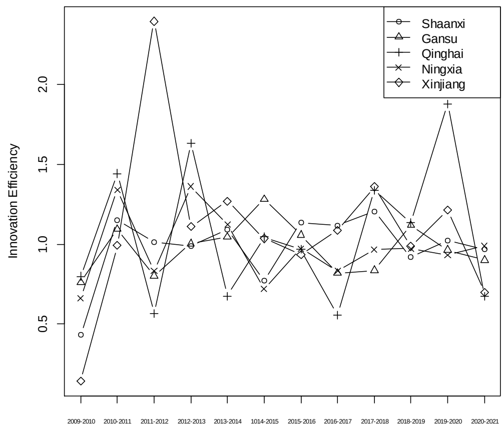

Figure 6. Northwest China

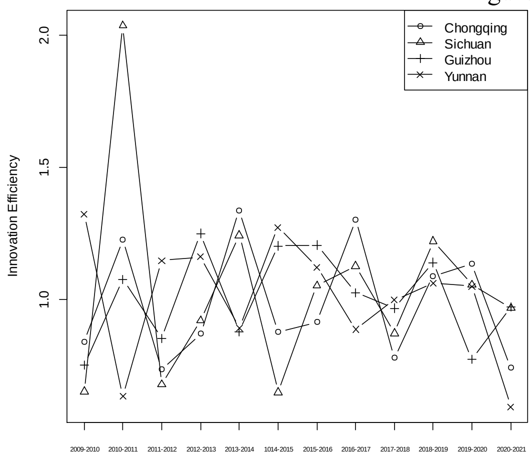

Figure 7. Southwest China

Figure 1 shows that this efficiency in the three northeastern provinces has remained relatively stable over the past decade. In Liaoning Province, there was a slight increase in 2016. Compared to 2015, the number of new product development projects and sales revenue from new product development in 2016 saw a significant rise, reflecting the initial effectiveness of the 735 enterprise technology innovation projects included in the key project plan of 2016. In other years, the innovation efficiency hovered around 1, with only the efficiency in 2010 being less than 1, indicating that the overall innovation level of high-tech industries in Liaoning Province is relatively high. In Jilin Province, this efficiency saw a significant increase in 2013, suggesting that the policies introduced by Jilin Province in 2013 to support enterprise technological innovation had noticeable effects. In Heilongjiang Province, this efficiency showed a slight improvement in 2017, reflecting the relatively slow impact of innovation awareness and innovation policies.

Figure 2 shows that this efficiency in Beijing, Tianjin, and Hebei has remained generally stable, fluctuating around 1 with minimal deviations. This stability is attributed to the coordinated development of the Beijing-Tianjin-Hebei commercial circle, where the policies of the three regions exhibit spatial synergy effects, mutually promoting the steady development of innovation efficiency. In contrast, the innovation efficiency of high-tech industries in the Inner Mongolia Autonomous Region has been consistently low. Only in 2017 did it show a significant improvement, while in most other years, the innovation efficiency was less than 1. This indicates that the impact of industrial innovation policies in this region has been minimal and that enterprises lack an innovative spirit.

Figure 3 shows that except for Henan Province, this efficiency in the other five provinces has remained around 1, with relatively small fluctuations. This indicates that the industrial innovation policies in these five central provinces share similarities and exhibit synergistic effects. In Henan Province, this efficiency experienced a significant increase in 2013, reflecting the remarkable results of allocating special funds to support the construction of major projects in strategic emerging industries. The increase in scientific and technological funding has stimulated enterprises' innovation output. Additionally, as a populous province, the improvement in the innovation awareness of technical talent in Henan has accelerated enterprises' innovation output.

Figure 4 shows that due to its location along the coastal belt, it benefits from unique developmental advantages, with the average of this efficiency exceeding 1. Among these, Shanghai and Zhejiang Province are in leading positions. In comparison, this efficiency in Shandong Province, Jiangsu Province, and Fujian Province has gradually approached 1, indicating a steady development trend. During the period from 2009 to 2015, this efficiency in the four provinces (excluding Shandong) exhibited significant fluctuations. However, on average, the innovation levels were relatively high. From 2015 to 2021, the fluctuations of this efficiency in the five provinces of East China were smaller, gradually stabilizing. This can be attributed to the synergistic development effects of the coastal economic belt, which have enhanced the innovation levels of coastal regions.

Figure 5 shows that Hainan Province has had an average innovation efficiency greater than 1 over the past decade. However, its efficiency has shown significant fluctuations, displaying a cyclical pattern. This indicates that the input of scientific and technological funding and personnel in Hainan exhibits periodic fluctuations, and the effectiveness of its industrial innovation policies also follows a cyclical trend. This efficiency in the Guangdong and Guangxi regions have experienced relatively small fluctuations, with efficiency gradually approaching 1. This can be attributed to the strong synergistic effects between these neighboring regions. However, the synergy between the Two Guang Regions and Hainan Province is relatively weak, which contributes to the differences in their innovation efficiency trends.

Figure 6 shows that this efficiency in the Northwest China has remained relatively stable over the past decade, fluctuating around 1. This indicates that the industries benefit from good synergistic effects. In particular, Shaanxi, Gansu, and the Ningxia Region have shown minimal fluctuations in innovation efficiency over the past decade. This reflects the sustainability and consistency of industrial innovation policies in these three areas. In contrast, Xinjiang Uygur Autonomous Region experienced a significant improvement in innovation efficiency in 2012, while Qinghai Province saw a substantial increase in 2020. These spikes can be attributed to a sharp decrease in scientific and technological investment during those years. However, the effects of previous high levels of investment began to materialize in those years, resulting in a low-input, high-output phenomenon. Following these spikes, both regions returned to more normal levels of innovation efficiency, aligning with typical investment-output dynamics.

Figure 7 shows that except for Sichuan Province, this efficiency in the other three regions has remained around 1, with relatively small fluctuations. This indicates that these three regions share similar industrial innovation policies, which exhibit synergistic effects in driving innovation efficiency. In Sichuan Province, this efficiency saw a significant increase in 2011, reflecting the remarkable results of the "611 Plan", which was the province's strategic emerging industries development plan. The substantial increase in scientific and technological fundings acquired by enterprises have effectively promoted their innovation productivity. Additionally, as the developmental core of the Southwest region, Sichuan benefits from national policy support and plays a leading role in driving innovation and industrial growth in the region.

Global Analysis

The innovation efficiency and decomposition of high-tech industries in 30 regions of China are shown in Figure 8.

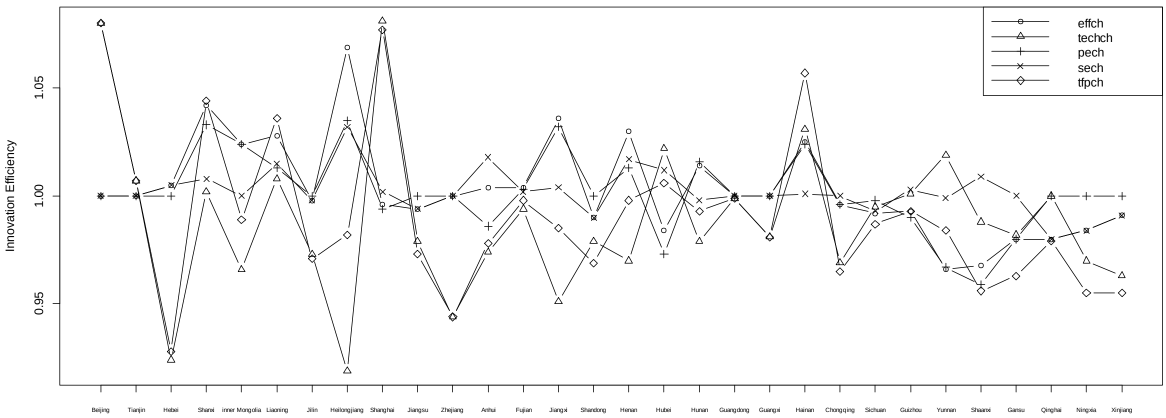

Figure 8. Overall efficiency values and decomposition of innovation efficiency in high-tech industries in 30 regions

According to Figure 8, over the past decade, the fluctuation trends of total factor productivity (TFP) and the technological progress index in high-tech industries across 30 regions are almost consistent. In Beijing and Shanghai, the TFP is significantly greater than 1, indicating that the improvement in TFP is mainly driven by technological progress. In contrast, the increase in TFP in Shanxi Province and Liaoning Province is attributed to improvements in technical efficiency. Since the differences in scale efficiency indices among the 30 regions are relatively small, the fluctuation trends of the technical efficiency index and the pure technical efficiency index are essentially consistent. However, the fluctuation amplitude of the technical efficiency index is smaller than that of the technological progress index, which results in the overall consistency between the fluctuation trends of

TFP and the technological progress index. From the perspective of regional differences TCP in most areas in Northwest, Southwest, Northeast, and Central China are less than 1. This indicates that the innovative performance of these industries is relatively poor, and there is still a need to strengthen innovation awareness.

SPATIAL EFFECTS

Variable Selection

Factors influencing the innovation efficiency of high-tech industries primarily include six key dimensions: regional development level, regional education level, openness of the region, regional urbanization level, government support, and the proportion of technical talents. The specific measurement criteria[17] for these factors are in Table 3.

Table 3. Measurement criteria for factors

Factors	measurement criteria
government support	The Proportion of Government Science and Technology Funding in the Total Regional Science and Technology Funding Raised
the proportion of technical talents	The Proportion of Regional Full-Time Equivalent R&D Personnel in the National Total Full-Time Equivalent R&D Personnel
openness of the region	The Proportion of Regional Total Import and Export Trade in Regional GDP
regional development level	The Proportion of Regional GDP in National GDP
regional education level	The Proportion of Students Enrolled in Higher Education Institutions in the Regional Total Population
regional urbanization level	The Proportion of Urban Population in the Regional Total Population

Model Construction

The Panel Spatial Lag Model (SLM) is expressed as Equation (6).

$$M_{it} = \rho\sum_{j=1}^{N} w_{ij}M_{jt} + \beta_1 GS_{it} + \beta_2 PT_{it} + \beta_3 OL_{it} + \beta_4 DL_{it} + \beta_5 EL_{it} + \beta_6 UL_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

In Equation(6), M is the dependent variable-technological innovation productivity, w is the spatial weight matrix, ρ is the coefficient of the spatial lag term of the dependent variable, GS denotes government support, PT denotes proportion of technical talents, OL denotes openness of the region,DL denotes regional development level, EL denotes regional education level, UL denotes urbanization level, β_i denotes coefficient of the independent variables, μ_i denotes individual fixed effects.

The Spatial Error Model (SEM) is expressed as Equation (7):

$$M_{it} = \beta_1 GS_{it} + \beta_2 PT_{it} + \beta_3 OL_{it} + \beta_4 DL_{it} + \beta_5 EL_{it} + \beta_6 UL_{it} + \mu_i + \lambda\sum_{j=1}^{N} w_{ij}U_{jt} + \varepsilon_{it} \tag{7}$$

In Equation (7), U is the Error term,λis the Coefficient of the spatial lag term of random disturbances, other variables are as defined above.

Further extending to the Spatial Durbin Model (SDM), the model is expressed as Equation (8):

$$\begin{aligned} M_{it} &= \rho\sum_{j=1}^{N} w_{ij}M_{jt} + \beta_1 GS_{it} + \beta_2 PT_{it} + \beta_3 OL_{it} + \beta_4 DL_{it} + \beta_5 EL_{it} + \beta_6 UL_{it} + \mu_i + \varepsilon_{it} \\ &+ \delta_1\sum_{j=1}^{N} w_{ij}GS_{it} + \delta_2\sum_{j=1}^{N} w_{ij}PT_{it} + \delta_3\sum_{j=1}^{N} w_{ij}OL_{it} + \delta_4\sum_{j=1}^{N} w_{ij}DL_{it} + \delta_5\sum_{j=1}^{N} w_{ij}EL_{it} + \delta_6\sum_{j=1}^{N} w_{ij}UL_{it} \end{aligned} \tag{8}$$

In Equation (8), δ_i is the Coefficient of the spatial lag terms of the independent variables, other variables are as defined above.

Empirical Analysis of Results

The results of the fixed-effects model for the SLM are presented in Table 4.

Table 4. Fixed-effects of the panel SLM model

Factors	Panel SLM Model			
	Mixture Model	Fixed space	Fixed time	Double fixed
government support	1.085(0.000***)	-0.828(0.418)	0.580(0.048**)	-0.741(0.455)
the proportion of technical talents	-4.859(0.138)	-9.426(0.321)	-0.891(0.781)	-9.331(0.303)
openness of the region	-0.325(0.088*)	-0.264(0.557)	-0.131(0.560)	-0.300(0.616)
regional development level	8.021(0.038**)	-13.121(0.430)	0.967(0.808)	-18.936(0.282)
regional education level	-19.430(0.006***)	19.757(0.495)	-15.710(0.024**)	3.313(0.906)
regional urbanization level	1.841(0.000***)	-2.592(0.130)	0.710(0.254)	-0.239(0.947)
spatial lag term	0.263(0.018**)	0.031(0.825)	-0.409(0.014**)	-0.447(0.008***)
LM-lag	1.280(0.258)	0.004(0.948)	1.989(0.158)	0.734(0.391)
Robust LM-lag	36.916(0.000***)	0.015(0.902)	4.077(0.043**)	0.223(0.636)
LM-err	1.606(0.205)	0.004(0.945)	0.994(0.319)	0.689(0.406)
Robust LM-err	37.242(0.000***)	0.015(0.900)	3.083(0.079*)	0.178(0.673)
Hausman	6.946(0.034) **	-4.395(0.733)	-22.599(0.002***)	-24.491(0.000***)

*Indicate significance at the 10% level, **indicate significance at the 5% level, *** indicate significance at the 1% level.

Table 4 shows that the mixed-effects model shows the best regression performance. Except for the coefficient of technical talent proportion, which is not significant at the 10% level, all other variables are significant. Under the spatial fixed effects, none of the influencing factors are significant, indicating poor regression performance. Under the time-fixed effects, only government support, regional education level, and spatial lag terms are significant, while other variables are not significant, indicating relatively poor regression performance. Under the two-way fixed effects, only the spatial lag term is significant, but the overall regression performance is poor.

The LM (Lagrange Multiplier) test results suggest that neither the spatial fixed effects nor the two-way fixed effects models pass the test ($p>0.05$). Conversely, the mixed-effects model and the time-fixed effects model show significance under the Robust LM-lag and Robust LM-err tests at the 10% level. Therefore, the mixed-effects approach in the Panel SLM model is preferable.

The results of the fixed-effects model for the SEM are presented in Table 5.

Table 5. Fixed-effects of the panel SEM model

Factors	Panel SEM Model			
	Mixture Model	Fixed space	Fixed time	Double fixed
government support	1.325(0.000***)	-0.836(0.414)	0.599(0.037**)	-0.454(0.643)
the proportion of technical talents	-5.390(0.102***)	-9.410(0.321)	-1.041(0.754)	-9.171(0.303)
openness of the region	-0.473(0.010***)	-0.257(0.567)	-0.174(0.437)	-0.477(0.434)
regional development level	9.521(0.013**)	-13.053(0.434)	1.199(0.764)	-21.723(0.204)
regional education level	-22.025(0.002***)	19.831(0.494)	-15.801(0.021**)	-0.044(0.998)
regional urbanization level	2.383(0.000***)	-2.625(0.126)	0.858(0.163)	0.852(0.810)
spatial lag term	0.136(0.317)	0.025(0.858)	-0.465(0.006***)	-0.504(0.003***)
LM-lag	11.780(0.001***)	0.022(0.882)	6.005(0.014**)	2.120(0.145)
Robust LM-lag	24.468(0.000***)	0.002(0.965)	0.577(0.447)	0.007(0.931)
LM-err	1.667(0.197)	0.041(0.839)	7.209(0.007***)	7.498(0.006**v)
Robust LM-err	14.355(0.000***)	0.021(0.885)	1.781(0.182)	5.385(0.020**)
Hausman	-0.944(0.995)	-7.049(0.423)	-30.911(0.000***)	-32.382(0.000***)

Table 5 shows that the conclusions are consistent with those of the SLM model. The mixed-effects model demonstrates the best regression performance: all variables are significant except for the coefficient of the spatial lag term at the 10% level. Moreover, compared to SLM, the mixed-effects model in SEM is more statistically significant. LM test results also reveal that the SEM model's mixed-effects model performs better overall. The mixed-effects model passes all tests, except for the LM-err test in some cases. Hence, among fixed-effects configurations, the mixed-effects model of SEM is optimal.

The random-effects results for both SLM and SEM are summarized in Table 6.

Table 6. Random-effects of panel SLM and SEM models

Factors	Panel SLM Model	Panel SEM Model
Constant	1.100(0.000***)	1.144(0.000***)
government support	0.445(0.139)	0.475(0.144)
the proportion of technical talents	-1.859(0.580)	-1.404(0.707)
openness of the region	0.001(0.994)	0.013(0.948)
regional development level	1.962(0.642)	1.485(0.762)
regional education level	-12.425(0.088*)	-15.727(0.050**)
regional urbanization level	0.345(0.551)	0.500(0.388)
spatial lag term	0.046(0.742)	0.030(0.833)
teta	0.996(0.000***)	0.000(0.999)

Table 6 shows that in the random-effects results of the Panel SLM model, only the impact of regional education level is significant at the 10% level, while other variables are not. Similarly, the SEM model's random-effects results are consistent with SLM, where only regional education level's impact at the 5% level is significant.

Table 7. Fixed and random-effects of the panel SDM Model

Factors	Fixed Effects				Random-Effects
	Mixture Model	Fixed space	Fixed time	Double fixed	
government support	0.555 (0.092*)	-1.189 (0.282)	0.262 (0.426)	-0.279 (0.800)	0.492 (0.141)
the proportion of technical talents	-3.246 (0.423)	-12.243 (0.229)	-3.618 (0.358)	-10.455 (0.292)	-2.457 (0.550)
openness of the region	-0.011 (0.963)	0.016 (0.979)	-0.243 (0.361)	-0.205 (0.762)	-0.060 (0.820)
regional development level	4.275 (0.351)	0.329 (0.987)	3.168 (0.480)	-3.488 (0.860)	3.084 (0.513)
regional education level	-11.724 (0.136)	24.309 (0.442)	-17.805 (0.021**)	17.390 (0.572)	-11.486 (0.145)
regional urbanization level	0.437 (0.546)	-2.438 (0.536)	1.627 (0.039**)	0.788 (0.843)	0.543 (0.459)
Lagged government support	1.885 (0.014**)	6.849 (0.068*)	0.307 (0.844)	9.021 (0.053*)	0.488 (0.751)
Lagged proportion of technical talents	-18.802 (0.182)	-8.874 (0.728)	0.612 (0.972)	-10.211 (0.696)	-6.150 (0.738)
Lagged regional openness level	-0.016 (0.976)	-1.687 (0.250)	-1.454 (0.154)	-3.680 (0.177)	0.146 (0.799)
Lagged regional development level	30.655 (0.071*)	-19.665 (0.754)	-9.143 (0.737)	-131.262 (0.171)	8.129 (0.766)
Lagged regional education level	-10.459 (0.747)	-24.312 (0.768)	-97.158 (0.045**)	-46.308 (0.644)	0.506 (0.988)
Lagged urbanization level in the region	0.632 (0.717)	-0.644 (0.913)	7.544 (0.045**)	21.361 (0.128)	-0.514 (0.801)
spatial lag term	0.028 (0.841)	-0.012 (0.929)	-0.495 (0.003***)	-0.330 (0.046**)	0.012 (0.929)
Constant	/	/	/	/	1.029 (0.299)
teta	/	/	/	/	0.996 (0.000***)
Wald-lag	12.043 (0.061*)	8.292 (0.217)	6.768 (0.342)	11.124 (0.084*)	1.212 (0.976)
Wald-err	14.125 (0.028**)	8.197 (0.224)	5.148 (0.524)	10.704 (0.098*)	0.369 (0.999)

Finally, based on Tables 4-6, the regression results of the fixed effects in the panel SLM model and panel SEM model indicate that the mixed effects model performs better. Therefore, when comparing fixed effects and random effects, even if the Hausman test for spatial fixed effects or temporal fixed effects suggests selecting fixed effects, it should not be adopted. The focus should instead be on comparing the mixed effects model under fixed effects and random effects. For the panel SLM model, the p-value of the Hausman test for the mixed model is less than 0.05, leading to the selection of the fixed effects model. For the panel SEM model, the p-value of the Hausman test for the mixed model is greater than 0.05, leading to the selection of the random effects model.

A comparative analysis between fixed-effects and random-effects reveals that for both SLM and SEM, the mixed-effects fixed model performs better. Ultimately, the Panel SLM mixed-effects model offers the best goodness of fit.

The fixed-effects and random-effects results for the SDM model are shown in Table 7[18].

Table7 shows that the mixed-effects fixed configuration in the SDM model shows relatively weak regression performance, with only government support and some interaction terms being significant at the 10% level. Moreover, in the random-effects model, none of the key variables are statistically significant, further indicating poor model fit. The Wald test[19] results reveal that the mixed-effects model under fixed effects shows higher levels of significance compared to random-effects models at the 10% level, but not as robust at the 5% level. This suggests limited applicability of the SDM model. Simplification to SLM or SEM may yield better results.

Combining the results of SLM, SEM, and SDM, the mixed-effects fixed model of SLM delivers the best goodness of fit and is most applicable. The model expression[20] is expressed as Equation(9).

$$M_{it} = 0.263\sum_{j=1}^{N} w_{ij} M_{jt} + 1.085GS_{it} - 4.859PT_{it} - 0.325OL_{it} + 8.021DL_{it} - 19.43EL_{it} + 1.841UL_{it} + \mu_i + \varepsilon_{it} \quad (9)$$

In Equation (9), M represents innovation efficiency in high-tech industries, and all other variables retain their previous meanings. It is noted that original data expressed as percentages were scaled by a factor of 100 to maintain significance levels in the final model.

In this model, since the original data for regional development level, regional education level, regional openness level, regional urbanization level, local government support, and the proportion of technical talent are expressed as percentages, these corresponding influencing factors need to be multiplied by 100 in the final selected model, while their significance remains unchanged.

From the analysis of the model's significance, its economic implications can be observed. local government support, regional economic development level, and regional urbanization level have a positive spatial effect on the innovation efficiency of high-tech industries, while the proportion of technical talent, regional openness level, and regional education level exhibit a spatial negative effect. The coefficient of the spatial error term is 0.263, indicating that the innovation efficiency demonstrates a significant spatial spillover effect. This suggests that the innovation efficiency of high-tech industries in neighboring provinces has a notable clustering characteristic. From a spatial perspective, this indicates that the local government support, regional economic development level, and regional urbanization level among the 30 regions can significantly enhance the innovation efficiency of high-tech industries. However, regional openness level and regional education level exhibit a significant inhibitory effect, which reflects the substantial regional disparities in openness level and education level among the 30 regions. Therefore, narrowing these regional disparities is essential to gradually highlight the positive effects of openness level and education level.

CONCLUSIONS

This study utilizes the DEA-Malmquist model to calculate the efficiency of innovation in fields with high technology in 30 regions over the past decade and conducts a regional difference analysis. The results show that This efficiency in the commercial circle including Beijing, Tianjin and Hebei and china’s coastal regions is relatively higher compared to others. This indicates that regional economic development contributes to the higher innovation efficiency. In other regions, the overall innovation efficiency values fluctuate around 1, indicating relatively stable development. However, in some specific regions, innovation efficiency has been improved under the influence of industry-related innovation policies or plans, though these effects are mostly short-term and have not shown long-term impacts.

Furthermore, the overall high-tech innovation efficiency in different regions of China over 13 years. The results reveal that the regional differences in the technical efficiency index are mainly caused by different pure technical efficiency index. However, the regional differences in the technical efficiency index are relatively small, the regional differences in total factor productivity are primarily driven by differences in the technological progress index. This suggests efforts should focus on promoting technological progress.

Based on the regression results of spatial effects, a comparison of the panel SLM, SEM, and SDM models reveals that the panel SLM model is more suitable for analyzing spatial effects. Additionally, government support, economic development, and urbanization are spatially positive to innovation efficiency, while technical talent, openness, and education exhibit negative spatial effects. The reasons behind these findings are analyzed, and the following recommendations are proposed.

Firstly, it is essential to leverage regional advantages in high-tech industry development and promote coordinated development within commercial clusters to gradually reduce regional disparities in innovation efficiency. At the same time, it is important to capitalize on each region's unique characteristics by implementing localized industrial policies and making effective use of national support policies for remote areas. For example, commercial clusters such as the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta can enhance their industrial innovation efficiency through synergistic effects. Meanwhile, regions like Northwest and Southwest China can fully utilize relevant national policies to maximize their impact.

Secondly, under the support of government-related industrial policies or planning, high-tech enterprises should fully utilize the benefits of these policies, improve their innovation mechanisms, and enhance employees' innovation awareness, thereby fundamentally increasing the enterprises' innovation capabilities. Most importantly, the focus should not be limited to short-term goals; instead, enterprises need to formulate innovation strategies suitable for long-term development to steadily improve innovation efficiency. The government should aim to establish a relatively balanced state of innovation investment across different regions. This involves reducing innovation investment in economically well-developed regions and, conversely, increasing innovation investment in less developed regions. Under the framework of new productivity, innovative production methods should be explored.

Thirdly, results shows each region should fully leverage the factors that generate positive spatial effects on the innovation efficiency of high-tech industries. Local governments should carefully review and interpret relevant support policies, steadily promote high-quality regional economic development, and enhance the level of urbanization. For factors that exhibit negative spatial effects, efforts should be made to identify the underlying causes and implement changes tailored to the region's specific innovation development needs.

From the perspective of technical talent, efforts should be made in two areas. On one hand, increase investment in technical talent and allocate appropriate funding for scientific research to ensure the smooth progress of technological projects. On the other hand, improve policies for attracting technical talent and enhance welfare benefits to build a high-level technical talent pool, thereby gradually attracting and retaining talent. From the perspective of openness, it is evident that many regions have relatively low levels of foreign trade, which Exerts negative influences on innovation. Therefore, it is crucial to strengthen technological exchanges and trade cooperation between regions to enhance innovation capacity. The negative spatial effect of education is primarily due to significant regional disparities in education levels. Thus, efforts should focus on narrowing the education gap between regions by improving access to quality education and resources, ultimately fostering a more balanced and supportive environment for innovation.

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