

Influence of Knowledge Spillover Effect of Industrial Transfer on Regional Economic Development and Gap

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Abstract: From the perspective of economic factor transfer brought about by Information Technology (IT), this study considers knowledge transfer as a primary factor that promotes technology transfer. The internal mechanism of the industrial spillover effect and the temporal trend of China's Gini coefficient are analyzed quantitatively. The Spatial Dubin Model (SDM) is the main analytical method, and the Moran index and regression statistics are used to test the model's feasibility, focusing on the impact of the Knowledge Spillovers (KS) effect on regional economic development and the gap under IT. The period from 2008 to 2021 is selected as the main research interval to examine the economic development gap across regions. The results show positive and negative spillover effects in the eastern and southern regions and the northern and southern regions, with significance at the 1% level. The development of the service industry and human capital in the central and western regions has several detrimental spillover effects, and most of the causes have minimal direct influence. The human capital and transportation infrastructure in the north have negative spillover effects. The impact of KSs is not significant and reflects negative impacts on some factors.

Keywords: Industrial transfer; knowledge spillover; regional economy; economic measure.

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1. Introduction

Since reform and opening-up, China's coastal regions have achieved rapid economic growth, while economic disparities between the Eastern Regions (ER) and Western Regions (WR), as well as between the Southern Regions (SR) and Northern Regions (NR), have become increasingly evident. To address regional development imbalance, the government has implemented various policy measures, among which Industrial Transfer (IT) plays a key role (Pulido-Fernández and Cárdenas-García, 2021; Chen et al., 2021). Beyond economic relocation, IT also generates spatial effects in technology and knowledge. Due to the spatial linkage among regional economies, knowledge and technology transfer during IT produces spillover effects that stimulate economic growth in host and neighboring regions (Audretsch et al., 2021; Caiazza et al., 2020; Arora et al., 2021). Compared with pure economic spillovers, Knowledge Spillovers (KS) are less constrained by capital location and often exhibit broader influence (Davies et al., 2021; Park et al., 2020; Ratten, 2021). In large-scale interregional IT, KS can promote regional development through indirect channels, providing a knowledge foundation for underdeveloped areas even in the absence of sufficient economic infrastructure.

2. Related Work

In recent years, research on the effects of KS has increased. Cristo-Andrade et al. (2020) analyzed the relationship between strategic entrepreneurship and KS using both qualitative and quantitative methods. Cetindamar et al. (2020) proposed analyzing KS effects in entrepreneurship ecosystems using emerging experimental knowledge bases. KS effects in Sydney were limited due to slow knowledge updates. Messeni and Murgia (2020) introduced a KS regulatory method for biotechnology and medical technology, highlighting the positive role of university specialization in regulating KS and fostering industrial innovation. Abbate et al. (2021) assessed the impact of academic knowledge transfer on innovation in the wine industry, suggesting that university knowledge transfer promoted technological innovation in medium- and low-tech enterprises. Bendickson et al. (2021) examined KS in entrepreneurial ecosystems, emphasizing the spillover effect as

a key driver of improvements in entrepreneurial environments with imperfect systems.

Further research into regional industrial economies has deepened. Liu et al. (2021) analyzed the relationship between economic development and industrial ecology in the Yangtze River basin, using coupling models and spatial regression. They found that economic development in the Yangtze River Delta influenced inland areas, thereby achieving coordinated development through the evolution of the industrial structure. Tripl et al. (2020) examined the green transformation of industries and proposed a model for analyzing regional economies. A theoretical foundation was established for green development. Khan (2022) explored the effects of primary industry growth on regional economic development, showing that managing internal changes in the primary industry could stimulate local economic growth. Dantas et al. (2021) explored the connection between economic sustainability and environmental development, demonstrating that industrial circular development supports sustainable economic growth.

Despite substantial research on spatial effects and industrial adjustments, there is limited research on the impact of knowledge transfer in regional development. The research focuses on the KS effects of IT and its impact on regional economic development and disparities.

3. Quantitative Analysis and Model Development of KS Effect Mechanism of IT

3.1. Quantitative Analysis of KS Effect Mechanism of IT

IT refers to the process by which industries relocate from one country or region to another in response to changes in resource supply or product demand. Unlike the simple reallocation of production factors, IT is often accompanied by the diffusion of advanced technologies, managerial experience, and organizational practices, thereby generating KS. In this study, KS is understood as the process through which knowledge is transmitted among different economic agents via non-market channels (such as firm interactions, labor mobility, and industrial linkages) during IT. Specifically, IT first facilitates the spatial diffusion of knowledge elements, after which KS influences regional economic development levels and inter-regional disparities through theory-driven channels, including demonstration, competition, labor mobility, and industrial linkage effects. This definition enables the analysis of KS in the context of IT to be consistently integrated with the spatial analysis of regional economic disparities. The internal mechanism of the impact of IT spatial KS on the regional economic gap is shown in Fig. 1.

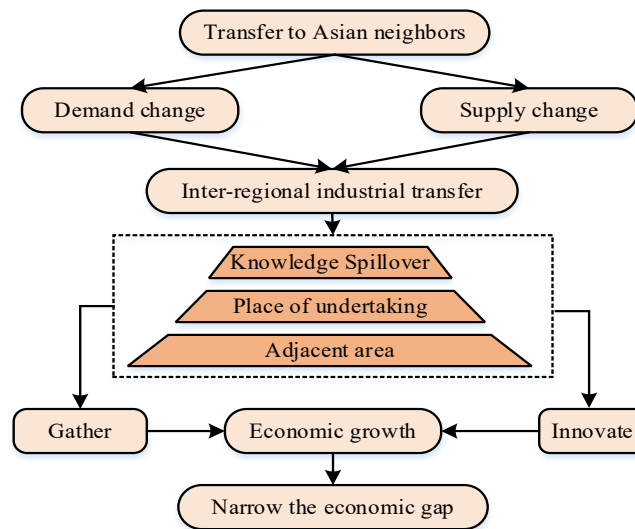


Fig. 1. Internal mechanism

In Fig. 1, IT has demonstrated its relevance to KS from the perspectives of changes in demand and supply and has further impacted the economy. The KS effect of IT extends beyond a single geographic area and includes the spatial dimension. IT is the carrier of factor allocation, through which various elements of spatial knowledge flow between regions, promoting knowledge interaction and exchange among different subjects and spatial spillover. The KS effect formed by IT through the demonstration effect, competition effect, human capital flow and industrial association affects the undertaking place itself. These factors also affect areas outside the undertaking site, especially adjacent areas. The specific influencing factors are shown in Fig. 2.

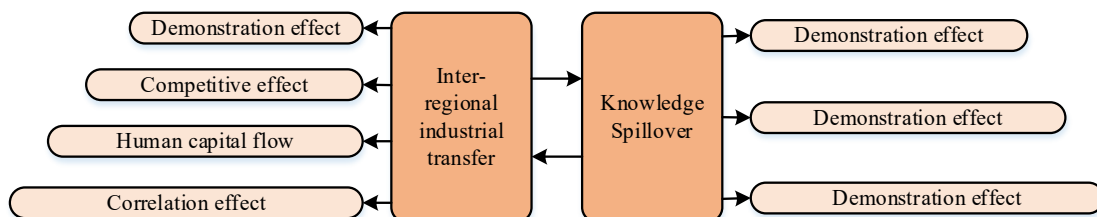


Fig. 2. Influence factor

The objectivity of regional information technology measurement depends on the chosen measurement methods and indicators. As the added value of industrial output across all regions of China increases, the inter-regional IT defined in the study is relative IT. Changes in the relative industrial scale across different regions are represented by shifts in the industrial center in the data. To investigate the dynamic changes in industrial geographical concentration in China over the past 20 years, the research uses MATLAB 6.5 to calculate the Gini coefficient of industrial space across 31 provincial administrative regions, as shown in Eq. (1).

$$Gini_i = \frac{1}{2n^2 \bar{P}_{ia}} \sum_{b=1}^n \sum_{a=1}^n |\bar{P}_{ia} - \bar{P}_{ib}| \quad (1)$$

In Eq. (1), O_{ia} represents the spatial Gini coefficient of industry i . P_{ia} and P_{ib} are the industrial shares of industry i in regions a and b . O_{ia} signifies the output value of industry i in a . n is the number of regions. The continuous rise in the Gini coefficient in the industrial sector indicates centralized industry transfer, while the continuous decline reflects decentralized industry transfer. Based on dynamic changes in IT within and across regions, the average concentration of the regional industry is calculated using industry data, as shown in Eq. (2).

$$Con_a = \frac{\sum_{i=1}^m P_{ab}}{m} \quad (2)$$

In Eq. (2), Con_a represents the average industrial concentration of the region a . P_{ab} is the share of industries i in regional a in the national industry. m is the number of industries. The average industrial concentration of the region a is used to measure the average share of the region's overall industry in the country. If the average concentration increases, the region is undertaking industries. Otherwise, the region is undergoing an industrial transition. The Gini coefficient of industrial space is shown in Fig. 3.

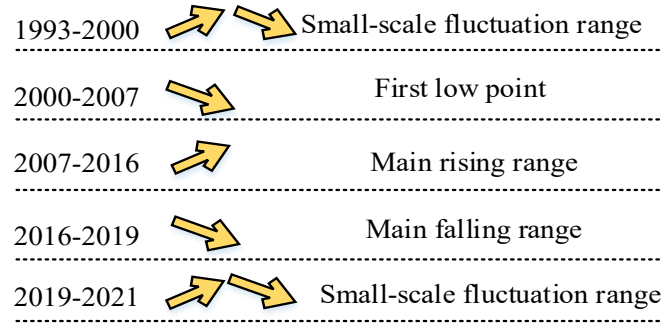


Fig. 3. Gini coefficient of industrial space

The changes in China's industrial spatial layout around 2007 show obvious phased characteristics. It has experienced three processes: dispersion, agglomeration and dispersion. Overall, China's industrial sector is still in a decentralized transfer. In IT, the gap between regions has been widening. In view of the changing trend in the economic gap across regions, the study uses the Taylor index to analyze the gap between regions and within regions. To assess economic growth from a production perspective, the research uses regional per capita GDP. The Taylor index is shown in Eq. (3).

$$T = \sum_{j=1}^n \left(\frac{G_j}{G} \cdot \ln \frac{G_j / G}{p_j / p} \right) \quad (3)$$

In Eq. (3), j is a provincial administrative region. n indicates the number of regions. G represents total GDP. G_j represents the GDP of j province. p is the total population. p_j is the population of the provincial administrative region j . A high Taylor index indicates a large economic disparity. The overall economic volume is decomposed according to different division criteria. The economic gaps between the ER and the Central And Western Regions (CWR), SR and NR are analyzed, respectively. The decomposition formula of the Taylor index is shown in Eq. (4).

$$T = \sum_{r=1}^l \left(\frac{G_r}{G} \cdot \ln \frac{G_r / G}{p_r / p} \right) + \sum_{r=1}^l \frac{G_r}{G} \left[\sum_{j \in r} \left(\frac{G_j}{G_r} \cdot \ln \frac{G_j / G_r}{p_j / p_r} \right) \right] \quad (4)$$

In Eq. (4), r represents the area. l signifies the number of areas. G_r signifies the total GDP of region r . p_r is the total population of area r . The overall economic gap in China is shown in Fig. 4.

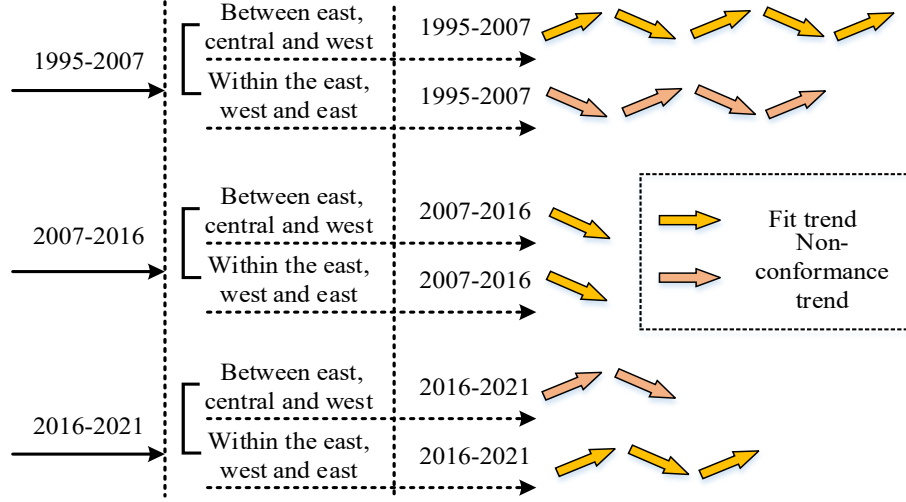


Fig. 4. China's overall economic gap

Changes in China's overall economic gap in the research area are largely driven by inter-regional effects between the eastern and western regions and intra-regional effects within each region. During the rising phase of the overall trend, the influence of the interaction between the eastern and western regions is more pronounced, leading to changes in the overall economic trend. During the period of decline, the impact of intra-regional effects in the eastern region and CWR is more obvious.

3.2. Construction of KS Effect Model of IT

The analysis shows that since 2004, China's industrial sector has undergone decentralized transfer, with the gap between the northern and southern regions gradually widening. The economic disparity between the central, WR, and ER has been a primary factor in the overall economic gap. Since 2014, the expanding gap within the ER and between the NR and SR has driven the increase in China's overall economic disparity. To examine the impact of IT and spatial KS on regional disparities, a spatial panel data model is used. The commonly used models include the Spatial Lag (SL) model, Spatial Error Model (SEM) and Spatial Dubin Model (SDM), with the SDM accounting for both endogenous and exogenous interactions, as shown in Eq. (5).

$$T_{jt} = \beta_0 + \omega WT_{jt} + \beta_1 Con_{jt} + \beta_2 Con_k_{jt} + \beta_3 S_{jt} + \beta_4 H_{jt} + \beta_5 M_{jt} + \beta_6 Tra_{jt} + \beta_7 U_{jt} + \sigma_1 WCon_{jt} + \sigma_2 WCon_k_{jt} + \sigma_3 WS_{jt} + \sigma_4 WH_{jt} + \sigma_5 WM_{jt} + \sigma_6 WTra_{jt} + \sigma_7 WU_{jt} + \varepsilon_{jt} \quad (5)$$

In Eq. (5), j is the provincial administrative region. t means time. β_i is the regression coefficient. σ_i signifies the SL of the explanatory variable. ω signifies the SL of the explained variable. Con_k represents KS from IT. S represents the development level of the service industry. H represents human resource capital. M represents the degree of industrial marketization. Tra means transportation infrastructure. U signifies the urbanization. W represents the spatial weight matrix. ε_{it} is a disturbance term subject to independent distribution. To measure knowledge stock, this study uses internal expenditure on industrial activities as a proxy, as it effectively reflects actual investments in technological development, process improvement, and knowledge accumulation within a region. Previous studies have widely recognized internal RandD and related industrial expenditures as appropriate indicators for capturing regional knowledge production capacity and knowledge stock, particularly in analyzing KS at the regional level. To ensure inter-temporal comparability across years, the relevant expenditure data are deflated using an appropriate price index published by the national statistical authorities, with 2004 adopted as the base year, thereby obtaining real measures of knowledge stock. The model indicator system is shown in Fig. 5.

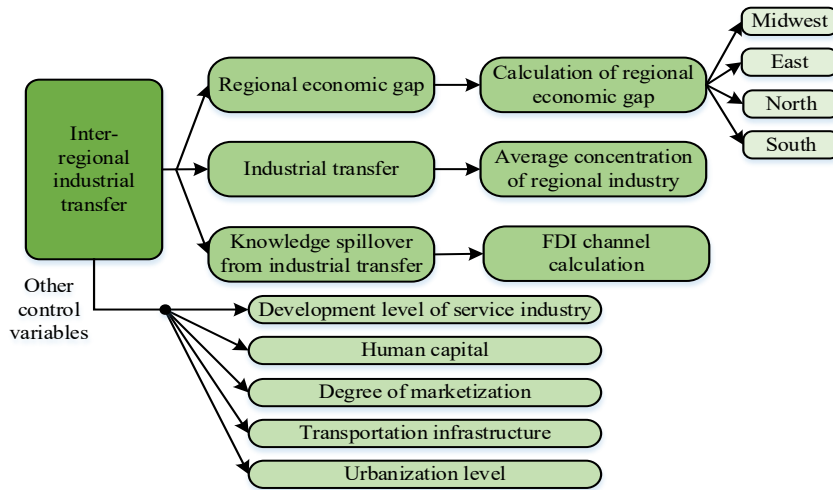


Fig. 5. Model indicators

Although the Theil index is widely used in regional inequality research due to its good decomposability, this study does not use it as the primary indicator for measuring economic disparities for the following reasons. First, this paper focuses on the spatial dependence of regional economic gaps and their spillover effects, rather than on the static decomposition of inequality levels. In this context, a GDP-per-capita-based gap measure is more suitable for integration with the spatial weight matrix, thereby directly characterizing the spatial propagation of regional disparities. Second, within a spatial econometric framework, continuous gap variables provide more intuitive economic interpretations for identifying spatial lag and spillover effects, thereby facilitating the analysis of spatial heterogeneity across regions. Therefore, the disparity measure in this study is consistent with the research objectives and the model specification.

4. The Impact of KS Effect on IT, Regional Economic Development and Gap

Prior to conducting the spatial econometric regression analysis, preliminary checks are performed on the basic distributional characteristics and temporal trends of the research variables. The results indicate that regional economic disparities, KS, and the control variables exhibit reasonable ranges and fluctuations over the sample period, with no apparent outliers or extreme distributions observed. In addition, correlation tests among the main explanatory variables indicate that the overall correlation is manageable and that no serious multicollinearity is present, thereby providing a sound data basis for subsequent model estimation.

The main period of overall economic change is from 2008 to 2021. Therefore, this main change interval is selected as the research interval. Before using the SEM, the researcher needs to test the economic gap between the provinces in the CWR of China and the ER, and between the northern provinces and the SR, to verify whether there is a significant spatial correlation between the two. The map of the regional economy under study is shown in Fig. 6.



Fig. 6. Map of the economic region

The research uses the spatial adjacency matrix and the Moran index to test the spatial correlation between the economic gap between the central and western provinces and the ER, and between the economic gap between the northern provinces and the SR, from 2008 to 2021. Table 1 displays the results.

Table 1. Spatial correlation test

Particular year	Northern			Midwest		
	Moran'I	Z statistic	P-value	Moran'I	Z statistic	P-value
2008	0.220	2.174	0.031	0.346	2.774	0.006
2009	0.011	1.942	0.050	0.321	2.593	0.010
2010	0.223	1.961	0.051	0.308	2.489	0.012
2011	0.204	1.705	0.088	0.295	2.381	0.016
2012	0.217	1.743	0.082	0.274	2.275	0.022
2013	0.245	1.962	0.053	0.262	2.132	0.035
2014	0.298	2.238	0.026	0.224	1.904	0.056
2015	0.296	2.227	0.024	0.160	1.460	0.141
2016	0.259	1.965	0.048	0.112	1.128	0.263
2017	0.174	1.480	0.139	0.103	1.045	0.290
2018	-0.224	-0.886	0.377	-0.014	0.281	0.782
2019	-0.273	-0.851	0.325	-0.059	0.103	0.764
2020	-0.312	-0.794	0.243	-0.127	-0.317	0.605
2021	-0.376	-0.623	0.205	-0.168	-0.569	0.531

In Table 1, the CWR and Moran's I are significantly positive from 2008 to 2014, and then gradually decrease from 2008 to 2021. The turning point is 2014, with a Moran'I of 0.224, a Z statistic of 1.904, and a P-value of 0.056. After 2014, the Moran'I significantly declines. In the NR, the Moran'I remains significantly positive from 2008 to 2021. It decreases from 2008 to 2011, and then increases from 2011 to 2014. The turning point is 2015, with a Moran'I value of 0.296, a Z statistic of 2.227, and a P-value of 0.024. After 2015, the Moran'I significantly declines. Based on these spatial correlation results, the study divides the analysis into different time periods for regression testing. The model regression results from 2008 to 2014 focus on the impact of IT spatial KS on the economic gap between the CWR and ER, while the results from 2008 to 2016 focus on the impact on the economic gap between the NR and SR.

In the spatial correlation test, the spatial correlation of the economic gap between the central and western provinces and the eastern provinces is objective. Therefore, the research is carried out from a spatial dimension. The data from 2008 to 2021 and from 2008 to 2014 are used to construct the OLS regression residuals for the LM test. Table 2 presents the SEM test results in the CWR.

Table 2. Test results of SEM in CWR

Model	2008-2014		2008-2021	
	Statistic	P-value	Statistic	P-value
Wald-SAR	12.47	0.0020	8.36	0.0152
Wald-SEM	11.63	0.0028	9.17	0.0103
LR-SAR	17.15	0.0165	22.58	0.0030
LR-SEM	17.24	0.0161	30.42	0.0001
LM SAR	3.049	0.082	7.824	0.005
Robust_LM SAR	8.172	0.004	6.816	0.008
LM SEM	0.048	0.826	2.335	0.125
Robust_LM SEM	5.164	0.024	1.329	0.252

The data from 2008 to 2021 and 2008 to 2014, the random effect SDM and fixed effect SDM are selected for the regression test. The regression outcomes are obtained through the test. Table 3 displays the results of the SDM in the CWR.

In Table 3, different periods show that the spatial auto-regressive coefficient ω is significantly positive at 1%, indicating a positive SSE for the economic gap between the CWR and the ER. Narrowing the economic gap between neighboring provinces and the ER is conducive to reducing the economic gap between the provinces and the ER.

Using data from two different time periods, the OLS regression residuals are constructed for the LM test. Table 4 presents the SEM test results in northern China.

Table 3. Regression results of SDM in CWR

/	2008-2014	2008-2021
Sample size	300	220
Con	-0.4462*** (0.000)	-0.2134*** (0.001)
Con_k	-0.0046 (0.804)	-0.0022 (0.889)
S	0.1025 (0.328)	-0.1218 (0.234)
H	-0.0329*** (0.001)	-0.0036 (0.725)
M	0.0082*** (0.004)	0.0032 (0.298)
Tra	-0.0035** (0.018)	-0.0039** (0.017)
U	-0.0218** (0.017)	-0.0505*** (0.000)
WCon	0.1398 (0.001)	-0.1845* (0.074)
WCon_k	0.0926*** (0.001)	0.0556*** (0.005)
WS	-0.3462* (0.094)	-0.0385 (0.820)
WH	0.0205 (0.221)	0.0227 (0.144)
WM	-0.0137** (0.026)	-0.0151** (0.016)
WTra	0.0035* (0.085)	0.0029 (0.220)
WU	0.0013 (0.934)	0.0265* (0.056)
ω	0.3136*** (0.000)	0.3046*** (0.000)
R ²	0.8178	0.7473
Log-L	1056.6147	1315.6870

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Test results of SEM in northern China

Model	2008-2016		2008-2021	
	Statistic	P-value	Statistic	P-value
Wald-SAR	29.95	0.0000	13.62	0.0010
Wald-SEM	29.39	0.0000	13.87	0.0012
LR-SAR	70.64	0.0000	57.05	0.0000
LR-SEM	72.83	0.0000	58.83	0.0000
LM SAR	6.012	0.015	2.568	0.108
Robust_LM SAR	15.256	0.000	16.069	0.000
LM SEM	0.641	0.426	0.014	0.913
Robust_LM SEM	9.895	0.003	13.506	0.000

According to Table 4, the test of the two periods is not a spatial model. Both the Wald and LR tests are significant. The data from the two periods are better suited to a regression test using the SDM model. Table 5 presents the SDM model regression results for northern China.

In Table 5, the regression results for the two periods show that the spatial autoregressive coefficient is significantly negative, suggesting that the economic disparity between the NR and the SR has a negative geographical spillover effect. The reduction of the economic gap between neighboring provinces and the SR has widened the economic gap between the province and the SR. Table 6 shows the direct effect, SSE and total effect of the SDM model in the CWR.

According to Table 6, the development of the service industry in the CWR has not passed the significance test for direct effect. Human capital, urbanization and transportation infrastructure have negative effects, with a significance of 1%. The marketization is positive, with a significance of 1%. In terms of spillover effects, the service industry, human capital, transportation infrastructure and urbanization do not pass the significance test. The marketization is negative, with a significance of 5%. Table 7 shows the direct effect, SSE and total effect of the SDM in northern China.

Table 5. Regression results of SDM in northern China

/	2008-2016	2008-2021
Sample size	180	220
Con	0.0713** (0.016)	0.0368 (0.141)
Con_k	-0.0055 (0.553)	0.0011 (0.918)
S	-0.0512 (0.383)	-0.0396 (0.472)
H	-0.0338*** (0.000)	-0.0370*** (0.000)
M	0.0103*** (0.000)	0.0074** (0.012)
Tra	-0.0024* (0.062)	-0.0022 (0.185)
U	0.0446*** (0.000)	0.0423*** (0.000)
WCon	0.0128 (0.846)	-0.1262** (0.027)
WCon_k	0.0658*** (0.000)	0.0576*** (0.000)
WS	-0.3731*** (0.006)	-0.0963 (0.476)
WH	-0.0125 (0.303)	-0.0282** (0.035)
WM	0.0124** (0.032)	0.0098 (0.122)
WTra	-0.0024 (0.243)	-0.0038 (0.122)
WU	-0.0497*** (0.001)	-0.0695*** (0.000)
ω	-0.2205* (0.052)	-0.2858*** (0.005)
R ²	0.5608	0.1727
Log-L	998.1265	1117.4119

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Direct effect, SSE and total effect of SDM model in CWR

/	2008-2014			2008-2021		
	Direct effect	SSE	Total effect	Direct effect	SSE	Total effect
Con	-0.4682*** (0.000)	-0.3902** (0.014)	-0.8583*** (0.000)	-0.2307*** (0.001)	-0.3232** (0.013)	-0.5539*** (0.001)
Con_k	0.0023 (0.912)	0.1279*** (0.000)	0.1400*** (0.001)	0.0017 (0.914)	0.0734*** (0.004)	0.0754*** (0.008)
S	0.0867 (0.394)	-0.4278 (0.134)	-0.3412 (0.292)	-0.1172 (0.251)	-0.1114 (0.637)	-0.2283 (0.427)
H	0.0322*** (0.001)	0.0136 (0.535)	-0.0185 (0.435)	-0.0015 (0.864)	0.0304 (0.135)	0.0288 (0.187)
M	0.0073*** (0.008)	-0.0152* (0.091)	-0.0078 (0.430)	0.0018 (0.515)	-0.0198** (0.020)	-0.0179* (0.062)
Tra	-0.0033** (0.020)	0.0032 (0.143)	-0.0001 (0.964)	-0.0035** (0.015)	0.0024 (0.403)	-0.0014 (0.582)
U	-0.0224** (0.012)	-0.0079 (0.645)	-0.0304* (0.061)	-0.0498*** (0.000)	0.0151 (0.354)	-0.0350** (0.015)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

According to Table 7, the development of the service industry in the NR has not passed the significance test for direct effect. Human capital has a negative effect, with a significance of 1%. The traffic infrastructure has a negative effect, and the significance reaches 10%. Marketization and urbanization have positive effects, with significance at 1%. For the spillover effect, the development of the service industry and human capital has a negative effect, with a significance of 1%. Urbanization has a positive effect at the 1% significance level. The marketization is positive, with a significance of 10%. The traffic infrastructure has a negative effect, with a significance of 10%. The direct effects of KS on the CWR and the NR are not significant. However, KS expands the economic gap between regions and does not necessarily bring positive results.

Table 7. Direct effect, SSE and total effect of SDM model in northern China

/	2008-2016			2008-2021		
	Direct effect	SSE	Total effect	Direct effect	SSE	Total effect
Con	0.0726** (0.016)	-0.0051 (0.932)	0.0677 (0.289)	-0.2307*** (0.001)	-0.3232** (0.013)	-0.5539*** (0.001)
Con_k	-0.0103 (0.275)	0.0602*** (0.000)	0.0498*** (0.000)	0.0017 (0.914)	0.0734*** (0.004)	0.0754*** (0.008)
S	-0.0255 (0.626)	-0.3091*** (0.008)	-0.3345** (0.022)	-0.1172 (0.251)	-0.1114 (0.637)	-0.2283 (0.427)
H	-0.0335*** (0.000)	-0.0049 (0.645)	-0.0385*** (0.001)	-0.0015 (0.864)	0.0304 (0.135)	0.0288 (0.187)
M	0.0096*** (0.000)	0.0088* (0.063)	0.0183*** (0.001)	0.0018 (0.515)	-0.0198** (0.020)	-0.0179* (0.062)
Tra	-0.0024* (0.098)	-0.0019 (0.345)	-0.0042*** (0.001)	-0.0035** (0.015)	0.0024 (0.403)	-0.0014 (0.582)
U	0.0478*** (0.000)	-0.0537*** (0.000)	-0.0048 (0.000)	-0.0498*** (0.000)	0.0151 (0.354)	-0.0350** (0.015)

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The empirical results across different regional samples and time periods indicate that the impact of KS under IT exhibits pronounced spatial heterogeneity in shaping regional economic disparities. In the CWR-ER sample, the spatial autoregressive coefficient is significantly positive during the period 2008-2014, suggesting that reductions in economic disparities among neighboring regions help narrow the gap between a given region and the eastern region, reflecting a clear positive spatial spillover effect. However, this effect weakens when the full sample from 2008-2021 is considered. By contrast, in the NR-SR sample, the spatial autoregressive coefficient is significantly negative in both periods, indicating that the spatial transmission of regional economic disparities between the northern and southern regions tends to diverge. The effect decomposition further shows that the direct effect of the KS is generally insignificant across regional samples, while its spatial spillover effect is significantly negative in some cases. This implies that knowledge diffusion does not necessarily reduce regional economic disparities and may instead exacerbate regional imbalance through the re-agglomeration of economic factors. These findings highlight the strong dependence of knowledge spillover effects on regional structural characteristics and spatial transmission pathways, an important contribution of this study relative to the existing literature.

5 Conclusion

In view of the current imbalance in China's economic development, the study identifies knowledge as a key driver of regional industrial development and analyzes its role in regional economic development. The study selects the spatial Dubin model as the primary model for analyzing the regional economic gap between 2008 and 2021. The findings demonstrate that the eastern and western spatial autoregressive coefficients are highly positive at the 1% significance level, indicating a positive SSE. The spatial autoregressive coefficients in the northern and southern regions are significantly negative, indicating a negative SSE. The direct effect of transportation infrastructure in the CWR is negative, with a significance of 1%. The marketization is positive, with a significance of 1%. Regarding the spillover effect, only marketization is negative and significant at the 5% level. In addition, human capital and transportation infrastructure in the NR are significantly negative at the 1% and 5% significance levels, respectively. Marketization and urbanization are significantly positive at the 1% significance level. Regarding the spillover effect, the development of the service industry and human capital is significantly negative at the 1% significance level. The urbanization is positive, with a significance of 1%. Marketization and transportation infrastructure have positive and negative impacts on economic growth, respectively, with significance at the 10% level. The direct effect of IT is conducive to reducing the regional economic development gap, but the KS effect is not significant and may have negative impacts on economic development.

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Author Contributions

Huijuan Sun contributed to conceptualization, resources, data curation, software, formal analysis, supervision, funding acquisition, validation, investigation, visualization, methodology, writing of the original draft, project administration, writing, reviewing and editing. Ning Bai contributed to conceptualization, resources, data curation, software, formal analysis, supervision, funding acquisition, validation, investigation, visualization, methodology, writing of the original draft,

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Declaration of Artificial Intelligence (AI) Tools

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