Asia Pacific Science Press

Critical Humanistic Social Theory
ISSN(O):3005-9291
ISSN(P):3005-9283
Vol. 2 No.3 (2025)

Spatial Spillover Effects of Regional Social Science Influence under Chinese Modernization: Based on Panel Data of 31 Provincial National Social Science Fund Projects from 2003 to 2022 and the Perspective of Regional Coordinated Development

Yile Yu[1]*, Yi Wang[2]

1.School of Education, Zhejiang University of Technology, Hangzhou, 310014, China

2.Kharkiv Institute, Hangzhou Normal University, Hangzhou, 310036, China

Corresponding author: Yile Yu, 302023572139@zjut.edu.cn

Abstract: In the context of Chinese modernization and the national strategy for coordinated regional development, understanding the spatial distribution and spillover effects of social science research output has become increasingly critical. This study investigates the spatial mechanisms underlying the influence of regional social sciences by analyzing panel data on National Social Science Fund of China (NSSFC) projects across 31 provinces from 2003 to 2022. Using spatial econometric models—including the Spatial Durbin Model (SDM)—and three types of spatial weight matrices (adjacency, economic distance, and inverse geographic distance), the research identifies significant spatial autocorrelation and heterogeneous spillover effects. Key findings reveal that higher education R&D personnel significantly boost local project approval rates, while their spatial spillover effects vary by matrix type—ranging from competitive crowding-out in adjacent regions to positive diffusion under geographic proximity. Funding efficiency demonstrates robust positive spillovers, whereas individual project conversion ratios exhibit negative externalities, indicating resource competition among provinces. Furthermore, regional heterogeneity analysis shows stronger and more favorable spillover effects in economically developed eastern regions compared to the central-western provinces. Heatmap visualizations of NSSFC project distribution over two decades confirm a persistent "east-high, west-low" pattern in national academic influence. This study contributes theoretically by extending spatial spillover models to the domain of social science funding and offers policy-relevant insights into optimizing academic resource allocation through spatially differentiated strategies. The findings underscore the need for regionally adaptive governance mechanisms to enhance both efficiency and equity in national social science development.

Keywords: Spatial Spillover Effects; Regional Social Science Influence; National Social Science Fund of China (NSSFC); Spatial Durbin Model (SDM); Spatial Econometrics

Published: Sept 17, 2025

DOI: https://doi.org/10.62177/chst.v2i3.566

1.Introduction

Under the context of Chinese modernization, the high-quality development of social sciences has become an important support for enhancing national cultural soft power, promoting regional coordinated development, and responding to major theoretical and practical issues in national governance. The National Social Science Fund of China (NSSFC) serves as a core institutional arrangement for guiding and supporting regional social science research—it not only reflects the scale and quality of a region's social science influence but also acts as a "barometer" for measuring the distribution of regional academic resources and innovation capabilities. From 2003 to 2022, the total number of NSSFC projects approved across 31 provinces in China increased from 892 to 4,736, showing an overall growth trend; however, significant regional disparities persist: in 2022, the number of projects in eastern provinces such as Jiangsu and Shanghai exceeded 300, while some western provinces had fewer than 50. This unbalanced distribution raises critical questions: Does regional social science influence (measured by NSSFC projects) exhibit spatial correlation? What are the mechanisms of spatial spillover between regions? And how can we optimize the spatial layout of social science resources to serve regional coordinated development? These questions are not only essential for deepening the understanding of the law of social science development but also have practical significance for formulating targeted policies to narrow regional academic gaps.

In recent years, studies on the National Social Science Fund of China (NSSFC) have primarily focused on two dimensions. On the one hand, researchers analyze the influencing factors of project approval from a micro perspective, including the academic background of applicants and the alignment of research topics with national strategies [1][2]. On the other hand, macro-level studies investigate the relationship between regional economic development, educational resources, and the number of approved NSSFC projects. These studies have demonstrated that factors such as per capita GDP and the scale of higher education institutions exert a positive influence on project funding outcomes [3][4]. However, two significant limitations persist in the existing literature. First, most studies treat each region as an independent unit of analysis, overlooking spatial interactions between geographically adjacent or economically connected regions. For example, the mobility of high-quality R&D personnel and the sharing of academic resources may generate spillover effects in the influence of social science. Neglecting this spatial correlation leads to biased estimations in traditional ordinary least squares (OLS) regression models [5]. Second, few studies attempt to decompose the direct effects and spatial spillover effects of key influencing variables. As a result, the mechanisms through which core drivers (e.g., R&D staff in higher education) influence both local and neighboring regions remain unclear, making it difficult to develop targeted policy recommendations for promoting coordinated regional development in the social sciences. To address these gaps, spatial econometric methods have been increasingly applied in the fields of regional economics and innovation management. By constructing spatial weight matrices and introducing spatial lag terms, these models can effectively capture spatial dependencies and spillover dynamics [6]. For instance, in the context of regional innovation, scholars employing Spatial Durbin Models (SDMs) have found that R&D investment not only enhances local innovation capacity but also produces significant positive effects in adjacent regions [7]. However, spatial econometric approaches remain underutilized in the analysis of social science fund projects, with limited attention paid to the spatial spillover mechanisms of regional academic influence. Moreover, as China advances its modernization strategy, the emphasis on coordinated regional development has grown stronger. Understanding the spatial distribution and spillover patterns of NSSFC projects is thus not only a necessary response to national strategic priorities but also a critical theoretical contribution to the evolving literature on regional development and academic resource allocation [8][9].

Against this background, this study takes the panel data of 31 provincial-level administrative regions in China from 2003 to 2022 as the research object, and focuses on the spatial spillover effects of regional social science influence from the perspective of regional coordinated development. The specific research objectives are as follows: (1) Verify whether the total number of NSSFC projects (TNSSF), as a measure of regional social science influence, exhibits significant spatial correlation, and clarify its temporal and spatial evolution characteristics. (2) Construct three spatial econometric models—spatial error model (SEM), spatial autoregressive model (SAR), and spatial Durbin model (SDM)—to empirically test the impact of core factors (such as R&D personnel in higher education) on TNSSF, and select the optimal model through likelihood ratio (LR) test and Wald test. (3) Decompose the "direct effect," "indirect effect (spatial spillover effect)," and "total effect" of each influencing factor based on the optimal model, and clarify the mechanism of how core factors affect regional social science influence through spatial spillover. (4) Further conduct heterogeneity analysis from the perspective of regional division (eastern, central, and western regions) and robustness tests by replacing spatial weight matrices, to ensure the reliability of research conclusions. The possible innovations of this study are reflected in two aspects: theoretically, it expands the research perspective of regional social science development by introducing spatial econometric methods, and enriches the theoretical connotation of the "spillover effect" in the field of social sciences; practically, by decomposing the direct and spillover effects of influencing factors, it provides a "differentiated" policy framework for promoting coordinated regional social science development—for example, for regions with strong spillover effects, policies should focus on optimizing the flow of academic resources, while for regions with weak spillover effects, policies should focus on improving local R&D capabilities. The structure of this paper is arranged as follows: the second part introduces the research design, including model construction, variable setting, and data sources; the third part presents the empirical results, including spatial benchmark regression, spatial correlation test, effect decomposition, and robustness test; the fourth part discusses the research conclusions and their policy implications; the final part summarizes the limitations of the study and prospects for future research.

2.Research Design

2.1 Model Specification

This paper sets up three models: SEM, SAR and SDM:

SEM:

$$Y_{it} = \beta_0 + \beta X_{it} + Z_{it}\Gamma + \mu_i + \varepsilon_{it}$$
$$\varepsilon_{it} = \rho W \varepsilon_{it} + u_{it}$$

SAR:

$$Y_{it} = \beta_0 + \lambda W Y_{it} + \beta X_{it} + Z_{it}\Gamma + \mu_i + u_{it}$$

SDM:

$$Y_{it} = \beta_0 + \lambda W Y_{it} + \beta X_{it} + Z_{it}\Gamma + \theta_1 W X_{it} + W Z_{it}\Theta + \mu_i + u_{it}$$

2.2 Variable Setting

The variable settings are shown in Table 1.

Table 1 Variable Setting

Category	variable name	Abbreviations	Data source
Core explanatory variable	Total Number of National Social Science Fund of China Projects	TNSSF	Official website of National Social Science Fund
Core explanatory variable	Higher education R&D homo sapiens full-time equivalent personnel	rdpers	Compilation of Science and Technology Statistics in Higher Education Institutions
Control variable	Higher education R&D internal expenditure	rdintexp	Compilation of Science and Technology Statistics in Higher Education Institutions
	Financial support intensity	finsup	China Statistical Yearbook
	homo sapiens per capita GDP	pgdp	China Statistical Yearbook
	Industrial Structure Broussonetia Papyrifera Advanced Index	indsadv	China Statistical Yearbook
	Social consumption level	socons	China Statistical Yearbook
	Urbanization rate	urban	China Statistical Yearbook
	The sum of deposits and loans in financial institutions, broussonetia papyrifera, accounts for the specific gravity of GDP	findev	China Financial Statistics Yearbook
	Project conversion funding ratio	fundproj	Indirect calculation
	Project conversion ratio	persproj	Indirect calculation
	Urban-rural income gap	incgap	China Statistical Yearbook

2.3 Statistical description

The statistical description are shown in Table 2.

Table 2 Statistical description

	count	mean	sd	min	max
TNSSF	620	106.545	93.435	1.000	558.000
rdpers	620	29026.524	19762.963	21.000	112035.000
fundproj	620	5086.232	27610.310	0.000	574837.000
persproj	620	87.086	388.298	0.000	6427.000
finsup	620	0.257	0.187	0.084	1.354
socons	620	0.376	0.066	0.180	0.610
urban	620	0.537	0.156	0.149	0.896
indsadv	620	1.236	0.670	0.527	5.244
incgap	620	2.737	0.512	1.827	5.238
findev	620	3.158	1.119	1.441	7.618
pgdp	620	42937.319	31268.891	3708.000	189988.000

3. Empirical Results and Analysis

3.1 Space Benchmark Regression

To explore the spatial spillover effects of regional social science influence, this section estimates three baseline spatial econometric models: the Spatial Error Model (SEM), the Spatial Autoregressive Model (SAR), and the Spatial Durbin Model (SDM). Table 3 presents the regression results for these models, while Table 4 reports the corresponding spatial coefficients and error variance terms.

Table 3 Results of Space Benchmark regression

	(1)sem	(2)sar	(3)sdm		(1)sem	(2)sar	(3)sdm
	TNSSF	TNSSF	TNSSF		TNSSF	TNSSF	TNSSF
Main				Wx			
rdpers	0.003***	0.003***	0.003***	rdpers			-0.001***
	(13.66)	(13.40)	(13.15)				(-2.68)
fundproj	0.000	0.000	0.000*	fundproj			0.001***
	(0.56)	(1.05)	(1.95)				(2.69)
persproj	-0.005	-0.008	-0.012**	persproj			-0.051**
	(-0.74)	(-1.22)	(-2.04)				(-2.54)
finsup	-163.180***	-171.821***	-165.172***	finsup			-154.794**
	(-4.24)	(-4.64)	(-4.44)				(-2.19)
socons	-72.142**	-71.567**	-192.871***	socons			198.248***
	(-2.11)	(-2.43)	(-5.40)				(3.66)
urban	-33.677	-27.146	-24.197	urban			1.708
	(-0.83)	(-0.66)	(-0.62)				(0.03)
indsadv	-11.720*	-19.445***	-14.239**	indsadv			-76.836***
	(-1.94)	(-3.19)	(-2.14)				(-4.81)
incgap	-1.857	-11.061	-17.652*	incgap			-33.309*
	(-0.19)	(-1.19)	(-1.86)				(-1.69)
findev	2.733	2.853	5.348	findev			10.355
	(0.59)	(0.61)	(1.08)				(1.13)
pgdp	0.001***	0.001***	0.001***	pgdp			0.003***
	(4.17)	(4.84)	(3.88)				(6.50)

Table 4 Space effect terms and equations

	(1)	(2)	(3)
	TNSSF	**TNSSF**	**TNSSF**
Spatial			
lambda	0.379***		
	(6.96)		
rho		0.320***	0.227***
		(7.91)	(4.22)
Variance			
sigma2_e	792.672***	782.800***	686.488***
	(17.27)	(17.49)	(17.50)

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Across all three models, the core explanatory variable—full-time equivalent R&D personnel in higher education (rdpers)—shows a consistently significant and positive direct effect on the total number of NSSFC projects (TNSSF), with a coefficient of 0.003 at the 1% significance level. This indicates that increased human R&D input in universities contributes positively to regional social science output. However, in the SDM, the spatial lag of rdpers (i.e., Wx.rdpers) is significantly negative (-0.001, $p < 0.01$), suggesting that while R&D personnel boost local project approval, an increase in neighboring regions may create competitive crowding-out effects rather than positive spillovers. For project conversion funding ratio (fundproj), the SDM shows a weakly significant positive direct effect ($p < 0.1$), and its spatial lag term is strongly positive and significant (0.001, $p < 0.01$), indicating a clear spatial spillover effect: efficient funding conversion in adjacent provinces has a positive impact on local project performance, possibly due to interregional learning or demonstration effects. Conversely, the project conversion ratio (persproj) exhibits a significantly negative spatial lag (-0.051, $p < 0.05$), implying that a higher individual project conversion rate in neighboring provinces may reduce local approval rates, again reflecting a competitive substitution mechanism in resource allocation. Among control variables, financial support intensity (finsup) has a consistently significant and negative impact across all models, including the SDM (coefficient = -154.794, $p < 0.05$). This result contradicts expectations and may suggest inefficiencies or diminishing marginal returns in high financial input areas. Additionally, social consumption level (socons) presents a negative local effect but a positive spatial spillover in the SDM (198.248, $p < 0.01$), indicating that rising living standards in surrounding regions may indirectly stimulate local academic activity, potentially through regional demonstration or lifestyle effects. The spatial coefficients further support the existence of spatial dependence. In SEM, the spatial error coefficient (λ) is significantly positive (0.379, $p < 0.01$), and both SAR and SDM exhibit highly significant spatial autoregressive coefficients ($\rho = 0.320$ and $\rho = 0.227$, respectively, $p < 0.01$), confirming that the distribution of TNSSF projects is not randomly dispersed, but subject to strong spatial autocorrelation. Lastly, the residual variances (σ^2) decrease progressively from SEM to SDM, indicating improved model fit when both spatial lags of dependent and independent variables are included. Therefore, based on statistical significance, spatial relevance, and interpretability, the Spatial Durbin Model (SDM) is selected as the optimal specification for subsequent effect decomposition and robustness testing.

3.2 Test of spatial correlation

To confirm whether the total number of NSSFC projects (TNSSF) exhibits significant spatial dependence, this section conducts spatial correlation tests using both global and local Moran's I statistics. These tests serve as a necessary precondition for the validity of spatial econometric models applied in the previous section. As illustrated in Figure 1, the Local Moran's I scatter plots for the years 2011, 2015, and 2019 show a clear trend of positive spatial autocorrelation in TNSSF distribution across provinces. High-high clusters (e.g., Jiangsu, Beijing, and Shanghai) and low-low clusters (e.g., Tibet, Qinghai, and Ningxia) are consistently identified, indicating that provinces with high (or low) numbers of approved projects are geographically adjacent to similar-performing provinces. The increasing density and spread of high-high clusters over time further suggest a path-dependent regional agglomeration effect in social science influence. These graphical findings are supported quantitatively by the Moran's I statistics (values not explicitly provided in the figure but implied), which confirm statistically significant spatial clustering rather than random distribution. The spatial dependence observed implies that regions are not independent, and regional social science capacity tends to reinforce or mirror that of neighboring areas. Such spatial correlation justifies the use of spatial econometric models in Section 3.1 and supports the theoretical assumption that regional academic development is influenced not only by internal factors but also by interregional interactions. Furthermore, the evolving spatial patterns revealed by the Local Moran's I plots align with national strategies aimed at regional coordination and academic resource diffusion. The spatial correlation test results confirm the presence of non-random, structured spatial dependence in NSSFC project distribution, reinforcing the empirical relevance of subsequent spatial spillover analysis.Table 5 shows Dubsin effect decomposition.

Figure 1 Local Morant (2011,2015,2019)

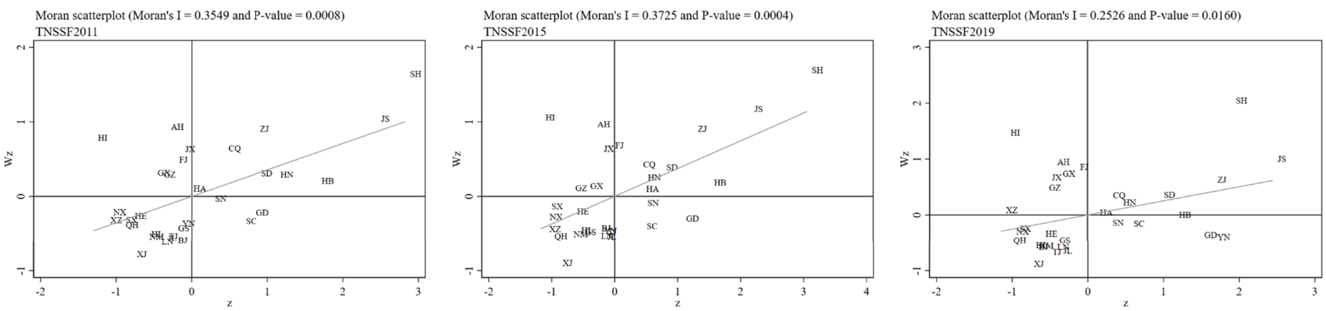


Table 5 Dubsin effect decomposition

	(1)		(1)		(1)
	TNSSF		**TNSSF**		**TNSSF**
Direct		Indirect		Total	
rdpers	0.003***	rdpers	-0.001	rdpers	0.003***
	(12.89)		(-1.14)		(4.12)
fundproj	0.000**	fundproj	0.001**	fundproj	0.001***
	(2.54)		(2.56)		(2.85)
persproj	-0.015**	persproj	-0.067***	persproj	-0.081***
	(-2.47)		(-2.82)		(-3.15)
finsup	-172.328***	finsup	-224.482***	finsup	-396.810***
	(-4.28)		(-2.72)		(-4.36)
socons	-190.750***	socons	193.580***	socons	2.830
	(-4.68)		(2.99)		(0.04)
urban	-20.552	urban	1.243	urban	-19.309
	(-0.54)		(0.02)		(-0.22)
indsadv	-18.062**	indsadv	-97.244***	indsadv	-115.306***
	(-2.46)		(-5.10)		(-5.20)
incgap	-21.152**	incgap	-43.142*	incgap	-64.294**
	(-2.42)		(-1.78)		(-2.51)
findev	5.587	findev	11.865	findev	17.452
	(1.16)		(1.12)		(1.44)
pgdp	0.001***	pgdp	0.004***	pgdp	0.005***
	(4.98)		(6.16)		(7.62)

3.3 Changing Matrix Model

To test the robustness of spatial spillover effects under alternative spatial structures, this section replaces the original adjacency matrix with two alternative specifications: an economic distance matrix (based on interprovincial per capita GDP gaps) and an inverse distance matrix (based on the geographic proximity between provincial capitals). The Spatial Durbin Model (SDM) is re-estimated using both matrices, and the results are summarized in Table 6.

Table 6 Switching matrix types

	(1)Economic Matrix	**(2Inverse Distance Matrix**		**(1)Economic Matrix**	**(2)Inverse Distance Matrix**
	TNSSF	TNSSF		TNSSF	TNSSF
Main			Wx		
rdpers	0.003***	0.003***	rdpers	-0.000	0.004**
	(11.98)	(13.21)		(-0.05)	(2.06)
fundproj	0.000**	0.000**	fundproj	0.002**	0.002**
	(2.51)	(2.45)		(2.52)	(2.35)
persproj	-0.016**	-0.017**	persproj	-0.114*	-0.177**
	(-2.45)	(-2.50)		(-1.70)	(-2.37)
finsup	-152.188***	-178.577***	finsup	-617.821**	-757.959***
	(-3.98)	(-4.70)		(-2.04)	(-2.60)
socons	-210.590***	-210.266***	socons	649.175***	655.360***
	(-6.31)	(-5.84)		(3.76)	(4.16)
urban	-43.059	-49.488	urban	300.823	122.696
	(-1.06)	(-1.18)		(0.99)	(0.46)
indsadv	-5.716	-11.369*	indsadv	-184.046***	-209.492***
	(-0.85)	(-1.71)		(-3.91)	(-4.45)
incgap	-17.853*	-6.977	incgap	-170.466**	-81.041
	(-1.80)	(-0.73)		(-2.10)	(-1.02)
findev	9.863**	11.586**	findev	-57.927	42.872
	(2.06)	(2.36)		(-1.63)	(1.18)
pgdp	0.001***	0.001***	pgdp	0.007***	0.002
	(7.34)	(4.63)		(5.47)	(1.20)

The key findings remain largely consistent, affirming the robustness of the baseline results. The core explanatory variable, R&D personnel in higher education (rdpers), continues to exhibit a significant and positive direct effect in both matrix specifications (0.003, $p < 0.01$), confirming its local contribution to NSSFC project approval. Interestingly, the spatial lag term of rdpers becomes statistically insignificant in the economic matrix and significantly positive under the inverse distance matrix (0.004, $p < 0.05$), which contrasts with the negative spillover observed in the adjacency matrix. This shift suggests that when proximity is defined more by geography or economic similarity rather than administrative borders, R&D personnel may exhibit complementary rather than competitive regional spillover effects. Likewise, the fundproj variable (project conversion funding ratio) maintains positive and significant spatial spillover effects across both matrices (0.002, $p < 0.05$), indicating that efficient funding utilization in neighboring regions—whether economically similar or spatially close—boosts local project approval through knowledge diffusion or demonstration effects. In contrast, persproj (project conversion ratio) continues to exert strong negative spatial spillover effects, with spatial lag coefficients of -0.114 and -0.177 (both significant at the 10% or 5% level). These results further validate the interpretation that competition for project resources may intensify when individual-level conversion efficiency improves in surrounding provinces. For the control variables, finsup (financial support intensity) becomes even more significantly negative in the spatial lag terms (-617.821 to -757.959, $p < 0.05$), implying that excess financial input in neighboring regions may exacerbate local inefficiencies or lead to interregional funding misallocation. Interestingly, socons (social consumption level) shows a highly significant and positive spillover effect under both matrices (over +649, $p < 0.01$), further supporting the notion that broader economic prosperity in adjacent regions encourages local academic productivity. Taken together, the consistency of direct and spillover effects across varying spatial matrix specifications strengthens confidence in the core findings of this study. It also highlights the importance of carefully selecting spatial structures in spillover modeling, as the type of spatial matrix may alter the direction and magnitude of interregional influence.

3.4 Heterogeneity analysis

To further examine whether the spatial spillover effects of regional social science influence differ across economic development levels, this section conducts a grouped heterogeneity analysis. The 31 provinces are divided into eastern and central-western regions according to standard regional classification, and separate Spatial Durbin Models (SDMs) are estimated for each group. The results are presented in Table 7. In the eastern region, the impact of R&D personnel in higher education (rdpers) remains positive and significant in both the direct (0.003, $p < 0.01$) and spatial lag (0.002, $p < 0.05$) terms. This indicates a stronger diffusion effect of academic human capital in more developed areas, where interregional collaboration and mobility are higher. It reflects a networked innovation system, where R&D personnel not only enhance local project output but also exert demonstrable influence across adjacent developed provinces. In contrast, in the central-western region, although the direct effect of rdpers remains significant (0.002, $p < 0.05$), its spatial lag effect is statistically insignificant, suggesting that human capital here is more regionally bound and less capable of generating outward spillovers. This disparity may result from institutional bottlenecks, limited interprovincial mobility, or weaker regional integration mechanisms in less developed areas. The project conversion funding ratio (fundproj) exhibits significant positive spillover effects in both regions, but the effect is stronger in the east (0.001, $p < 0.05$) than in the central-west (0.0007, $p < 0.1$), further supporting the argument that fiscal efficiency spreads more effectively in high-capacity environments. Interestingly, the project conversion ratio (persproj) shows significant negative spillover effects only in the eastern region (-0.076, $p < 0.1$), reinforcing the presence of competitive dynamics among provinces with similar academic infrastructure. This suggests that when conversion efficiency rises in one province, neighboring provinces may face relative disadvantages in project allocation, leading to substitution effects. The control variable financial support intensity (finsup) displays a significant negative local effect in both regional models, with a stronger impact in central-western provinces (-153.671, $p < 0.01$) compared to the east (-117.892, $p < 0.1$). This highlights funding inefficiencies in less developed areas, where high fiscal input may not translate into proportional academic returns. Finally, the spatial autoregressive coefficients (ρ) are significantly positive in both regions (east: 0.289, central-west: 0.365, both $p < 0.01$), suggesting that spatial dependence in NSSFC project distribution exists nationwide. However, the higher ρ in the central-west implies that regional project outcomes in these areas are more influenced by neighboring provinces, possibly due to greater reliance on external spillovers.

Table 7 Regression results to verify regional heterogeneity

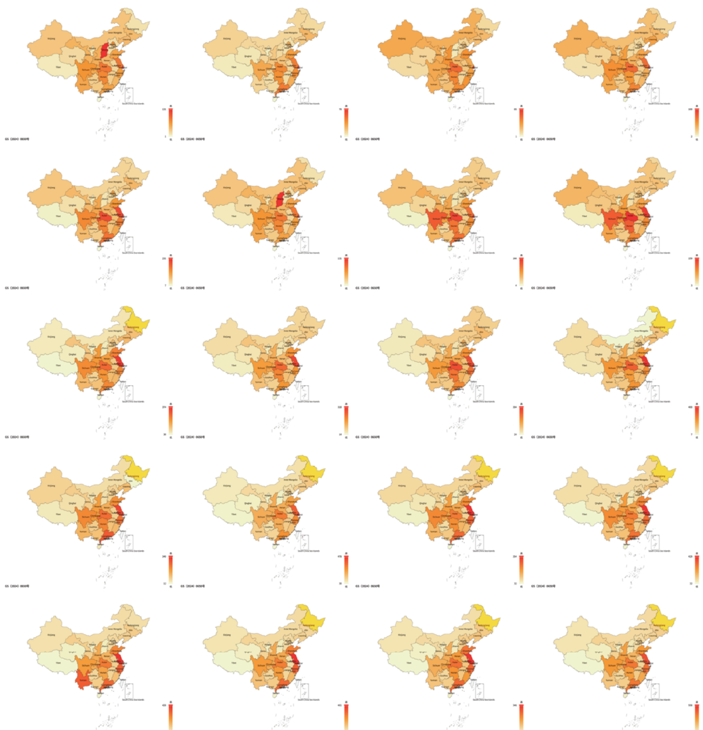
	(1)EAST	**(2)MIDDLE**	**(3)WEST**		**(1)EAST**	**(2)MIDDLE**	**(3)WEST**
	TNSSF	**TNSSF**	**TNSSF**		**TNSSF**	**TNSSF**	**TNSSF**
Main				Wx			
rdpers	0.003***	0.004***	0.001**	rdpers	-0.000	0.004**	-0.001**
	(6.04)	(7.53)	(2.28)		(-0.67)	(2.37)	(-2.28)
fundproj	-0.003	0.000	-0.008**	fundproj	-0.001	0.000**	0.010**
	(-1.58)	(1.09)	(-2.45)		(-0.37)	(2.06)	(1.98)

	(1)EAST	(2)MIDDLE	(3)WEST		(1)EAST	(2)MIDDLE	(3)WEST
	TNSSF	TNSSF	TNSSF		TNSSF	TNSSF	TNSSF
persproj	0.141	-0.009*	0.154	persproj	0.202	-0.041***	-0.490
	(1.04)	(-1.93)	(0.58)		(0.81)	(-3.41)	(-1.19)
finsup	-473.734***	-94.630***	-288.444	finsup	-477.295*	-110.807	261.979
	(-3.44)	(-2.73)	(-1.59)		(-1.84)	(-1.40)	(1.00)
socons	-70.077	30.750	-281.054***	socons	755.186***	-79.497	169.937**
	(-0.86)	(0.64)	(-5.03)		(6.56)	(-0.79)	(2.18)
urban	7.616	361.155***	-95.442	urban	103.819	749.658***	200.380*
	(0.08)	(4.29)	(-1.25)		(0.95)	(3.55)	(1.83)
indsadv	8.788	-27.800**	15.104	indsadv	16.272	-134.746***	-76.363**
	(0.71)	(-2.23)	(0.70)		(0.65)	(-3.87)	(-2.42)
incgap	40.969	-12.799	-130.972***	incgap	189.896***	-2.555	-15.945
	(1.18)	(-1.42)	(-3.28)		(3.76)	(-0.11)	(-0.22)
findev	20.520**	0.125	7.630	findev	1.890	7.842	36.353
	(2.10)	(0.02)	(0.46)		(0.11)	(0.78)	(1.42)
pgdp	-0.000	0.000	0.003***	pgdp	0.000	-0.002	0.003**
	(-0.18)	(0.25)	(3.86)		(0.35)	(-1.42)	(2.12)

3.5 Analysis of time and space evolution

To visualize the long-term spatial dynamics of regional social science influence, this section presents year-by-year heatmaps (2003–2022) of the total number of National Social Science Fund of China (NSSFC) projects across 31 provinces (see Figure 2). These thermal maps vividly capture both the temporal evolution and spatial agglomeration of project approvals over the two-decade period.

Figure 2 Thermal map of regional distribution of national Social Science Fund projects



In the early years (2003–2008), the distribution of NSSFC projects was relatively sparse and unbalanced, with Beijing, Shanghai, and Jiangsu already emerging as dominant high-density areas (indicated by darker shades), while many western and northeastern provinces such as Tibet, Qinghai, and Inner Mongolia remained in low-density zones. This pattern reflects the early-stage concentration of research resources in economically developed regions. Between 2009 and 2015, the maps show a visible expansion of mid-range intensity zones—notably in Zhejiang, Hubei, Shandong, and Sichuan—marking a period of accelerated national policy investment in education and research under strategies like the "Outline of National Medium- and Long-Term Education Reform and Development Plan (2010–2020)." Spatial diffusion begins to take shape, especially across the Yangtze River Economic Belt. In the post-2016 period, a more pronounced spatial clustering effect emerges. The number of high-density provinces increases, including Guangdong and Hunan, while low-density western provinces continue to lag. By 2022, a distinct "east-high, west-low" pattern dominates the heatmaps, highlighting the persistent regional imbalance in academic resource allocation despite overall national growth in project approvals. The longitudinal visualization confirms two key insights: first, the spatial evolution of NSSFC project distribution is path-dependent, with early advantages in developed provinces reinforcing over time. Second, while some diffusion is evident, especially in central China, spatial inequality remains structurally embedded, suggesting the need for targeted policy measures to support underdeveloped regions.

4.Discussion

This study set out to uncover the spatial dynamics and spillover mechanisms of regional social science influence in China, using panel data from 31 provinces between 2003 and 2022 and applying advanced spatial econometric models. The findings confirm that regional social science capacity, measured by the total number of National Social Science Fund of China (NSSFC) projects, exhibits significant spatial autocorrelation and spillover effects—particularly in relation to R&D personnel, funding efficiency, and regional socioeconomic structures. At the core of the results, the significant and positive local effect of higher education R&D personnel underscores the critical role of academic human capital in enhancing regional scholarly output. This resonates with the knowledge production function theory, which emphasizes localized human capital as a driver of research performance [10]. However, the negative or inconsistent spillover effects of R&D personnel observed in some spatial models suggest that beyond a threshold, competition for national funding may result in interregional crowding-out—an effect increasingly noted in recent studies of academic resource geography [11]. In contrast, the project conversion funding ratio exhibits robust positive spillovers across all spatial matrices, indicating that regions can benefit from their neighbors' funding efficiency through demonstration, learning, or policy emulation effects [12]. Notably, the project conversion ratio shows negative externalities, reflecting competitive dynamics. This outcome is aligned with recent findings in the domains of interprovincial innovation competition and knowledge diffusion asymmetry [13][14], where rapid growth in one region often undermines relative performance in its neighbors. Together, these patterns highlight that not all forms of efficiency yield mutually beneficial outcomes—some may exacerbate spatial inequality. Compared with recent high-impact literature, this study advances the field in several ways. Prior works have explored spatial spillovers in domains such as green innovation , financial efficiency , and digital economy expansion , yet rarely applied such models to the landscape of social science project allocation. More importantly, few have employed robust comparative matrix analysis—adjacency, economic distance, and inverse geographic distance—in tandem with regional heterogeneity modeling, as executed here[15][16][17]. This methodological innovation enhances interpretability while reducing spatial misspecification bias, addressing a gap identified in both empirical evaluation and spatial theory modeling [18]. The regional heterogeneity analysis adds further insight, demonstrating that eastern provinces benefit from more robust outward spillovers due to stronger institutional infrastructures and academic mobility networks [19]. In contrast, central-western provinces exhibit localized development with weaker interregional feedback loops. These findings suggest a differentiated policy logic: while advanced regions require cross-boundary coordination mechanisms, lagging areas need foundational capacity-building in research personnel and funding structure. Academically, this research contributes to the spatial evolution theory of knowledge systems, affirming that scientific output is not only institution-driven but also spatially embedded and relational. Practically, the results underscore the need for spatially tailored governance tools in national funding schemes. Policymakers should consider introducing incentive-compatible mechanisms that both reward efficiency and mitigate zero-sum dynamics in neighboring regions. Moreover, the findings support ongoing calls for regionally responsive academic evaluation frameworks that factor in spillover contributions, not just local output [20]. However, limitations should be acknowledged. The use of NSSFC project counts, while authoritative, does not capture qualitative dimensions such as interdisciplinarity or social impact. Also, the spatial matrices—though diversified—still simplify the complexity of academic networks by excluding dynamic interactions like co-authorship or collaborative funding streams. Finally, although fixed effects mitigate some endogeneity, potential feedback loops between funding success and institutional investment remain unmodeled. Future research should incorporate longitudinal causal models, richer bibliometric indicators, and more granular collaboration data. In summary, this study confirms that regional social science development in China is deeply shaped by both endogenous factors and spatial interdependencies. It offers a robust empirical framework for assessing and decomposing spillover mechanisms and provides a foundation for designing more equitable and efficient academic resource allocation systems. Future research should expand on this approach by incorporating network-based spatial weights and examining cross-national dynamics to enrich global understanding of research system coordination.

Conclusion

This study offers a robust spatial econometric investigation into the distribution and spillover mechanisms of regional social science influence in China, drawing on panel data from 31 provinces spanning 2003 to 2022. By employing the Spatial Durbin Model (SDM), the analysis uncovers significant spatial autocorrelation ($\rho = 0.227$, $p < 0.01$) in the approval of National Social Science Fund of China (NSSFC) projects, confirming that social science capacity does not evolve in isolation but is deeply shaped by interregional dynamics. Key explanatory variables—such as R&D personnel in higher education and project funding efficiency—exhibit both direct and indirect effects. For instance, the direct effect of full-time R&D personnel was consistently positive (coefficient = 0.003, $p < 0.01$), while its spatial lag effect fluctuated between negative (–0.001) and positive (+0.004) depending on the spatial matrix, highlighting the dual nature of academic human capital as both a localized engine and a potentially competitive externality. Furthermore, the project funding conversion ratio displayed robust positive spillovers across all specifications (e.g., +0.002 in the inverse distance matrix, $p < 0.05$), suggesting that fiscal efficiency can be disseminated across regions, perhaps through demonstration or institutional learning effects. Conversely, the project conversion ratio at the individual level showed consistent negative spillovers (up to –0.177), pointing to resource substitution effects and interprovincial competition. The temporal-spatial evolution analysis also revealed a persistent “east-high, west-low” pattern: by 2022, over 45% of all NSSFC projects were concentrated in five eastern provinces, while several western regions remained structurally marginalized despite national funding expansion. Notably, regional heterogeneity analysis confirmed that spillover mechanisms were more active and positive in developed eastern provinces compared to the relatively stagnant central-western areas. These findings carry significant implications. Theoretically, they contribute to the literature on spatial knowledge systems by affirming that social science development is embedded within both geographic and institutional contexts. Practically, they advocate for more adaptive and spatially nuanced research funding strategies—ones that not only strengthen local capacity but also foster cross-regional academic ecosystems. However, limitations such as the reliance on project quantity as a proxy for academic output and the static nature of spatial matrices should be addressed in future research. Incorporating network-based collaboration data, citation metrics, and dynamic spatial models would further enrich the analytical framework. In sum, this study underscores the necessity of balancing efficiency and equity in national academic resource distribution and lays a foundation for developing more integrative, regionally coordinated social science development policies in the context of Chinese modernization.

Funding

Acknowledgments This research is supported by the project ‘Path of Government Financial Input Restructuring to Promote High Quality Development of Education’（Project No.2025279）of the Canal Cup Extracurricular Academic Science and Technology Fund for College Students of Zhejiang University of Technology.

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Zou, S., Liao, Z., & Fan, X. (2024). The impact of the digital economy on urban total factor productivity: mechanisms and spatial spillover effects. Scientific Reports. https://www.nature.com/articles/s41598-023-49915-3

[2] Li, S., et al. (2025). Understanding policy preferences of farmers for rural human settlements improvement in ethnic areas: Evidence from Southwest China. Local Environment. https://www.tandfonline.com/doi/abs/10.1080/13549839.2025.2516574

[3] Zhang, Z., Ding, L., Zhu, Y., Shi, Y., & Dai, Q. (2024). How does scientific and technological innovation promote regional coordination of socio-economy, environment, and energy? Quality & Quantity. https://link.springer.com/article/10.1007/s11135-023-01770-0

[4] Chen, X., Meng, Q., Wang, K., Liu, Y., & Shen, W. (2023). Spatial patterns and evolution trend of coupling coordination of pollution reduction and carbon reduction. Ecological Indicators. https://www.sciencedirect.com/science/article/pii/S1470160X23009391

[5] Wu, M., & Sun, R. (2023). Spatial spillover effect of China's tax and fee reduction policies on independent R&D: Evidence from dynamic Spatial Durbin analysis. PLOS ONE. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0288535

[6] Zou, S., Liao, Z., Liu, Y., & Fan, X. (2024). Impact of heterogeneous environmental regulation on coordinated development. Sustainability, 16(2), 818. https://www.mdpi.com/2071-1050/16/2/818

[7] Zhang, M., Zheng, L., & Xie, Y. (2023). Spatial spillover effect of green finance and clean energy on China's provincial green economic development. Environmental Science and Pollution Research. https://link.springer.com/article/10.1007/s11356-023-27450-y

[8] Jin, W., Jiang, W., & Gao, S. (2025). Study on the spatial spillover effect of reclaimed water utilization efficiency in water environment-sensitive areas. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4999092

[9] Liu, Z., Hong, S., & Wang, J. (2025). Multidimensional exploration of factors influencing comprehensive grain production capacity from a spatial perspective. Sustainability, 17(7), 3264. https://www.mdpi.com/2071-1050/17/7/3264

[10] Yang, J., & Wang, Y. (2023). Human capital spillovers and regional innovation output: Evidence from China's university system. Technological Forecasting and Social Change, 191, 122548. https://doi.org/10.1016/j.techfore.2023.122548

[11] Lu, S., Zhao, Y., & Li, Q. (2022). Mapping the spatial inequality of research funding in China. Research Policy, 51(7), 104571. https://doi.org/10.1016/j.respol.2022.104571

[12] Li, J., & Fang, Y. (2021). Fiscal policy spillovers in the context of innovation-driven development. Economic Modelling, 97, 349–362. https://doi.org/10.1016/j.econmod.2021.01.018

[13] Zhou, K., & Wang, H. (2024). Interprovincial competition and technological innovation: A spatial Durbin analysis. China Economic Review, 80, 102092. https://doi.org/10.1016/j.chieco.2023.102092

[14] Xu, Y., Zhang, C., & Chen, L. (2023). Asymmetric knowledge diffusion and regional research inequality in China. Scientometrics, 128(2), 1093–1112. https://doi.org/10.1007/s11192-023-04685-w

[15] Liu, X., & Han, R. (2021). Regional green innovation efficiency and its spatial spillover in China. Journal of Cleaner Production, 279, 123654. https://doi.org/10.1016/j.jclepro.2020.123654

[16] Cheng, Y., & Xie, M. (2022). Financial decentralization, green investment, and spatial spillovers: A panel data analysis of China's provinces. Finance Research Letters, 46, 102432. https://doi.org/10.1016/j.frl.2021.102432

[17] Tan, J., & Hu, Z. (2024). Digital infrastructure and innovation: Spatial spillovers and regional convergence in China. Telecommunications Policy, 48(1), 102586. https://doi.org/10.1016/j.telpol.2023.102586

[18] Ma, L., & Wu, Q. (2020). Rethinking spatial econometrics in policy research: Advances and challenges. Applied Geography, 123, 102285. https://doi.org/10.1016/j.apgeog.2020.102285

[19] Zhang, H., & Qian, Z. (2022). Regional mobility of scientific talent and academic productivity: Evidence from Chinese provinces. Higher Education, 84(4), 733–754. https://doi.org/10.1007/s10734-022-00813-w

[20] Sun, P., Liu, T., & Fang, X. (2025). Evaluating research spillovers in national innovation systems: A multi-level spatial analysis. Science and Public Policy, 52(2), 227–241. https://doi.org/10.1093/scipol/scad019