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Research on the Role of Science Popularization in Regional Innovation: An Analysis from the Perspective of Science Popularization Personnel Elements

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Abstract

Although the social value of science popularization has been increasingly recognized, the specific role of science popularization in regional innovation remains inadequately explored in the existing literature. Most of the related research focuses on traditional factors such as R&D investment. To bridge this gap, this study empirically examines the impact of science popularization personnel on regional innovation by analyzing panel data from 30 provincial-level regions in China from 2013 to 2022. The study employs two-way fixed effects models for baseline analysis, and utilizes threshold regression models, explicitly selecting government funding for science popularization as the threshold variable, to investigate non-linear mechanisms.

The empirical results indicate that human capital investment in science popularization serves as a significant driver of regional innovation capacity, a conclusion that remains robust after addressing endogeneity and conducting rigorous reliability tests. Furthermore, the analysis reveals significant regional heterogeneity in China, with the marginal utility of human capital being most pronounced in the western regions, suggesting a higher potential for catch-up growth. Crucially, the study identifies a structural break: The promotional effect of human capital is contingent upon public funding. A significant threshold effect exists, where the impact of human capital intensifies substantially only after financial investment crosses a specific critical level.

Based on these findings, specific policy recommendations are drawn. Policymakers should prioritize the strategic allocation of science popularization talent towards the western regions in China to leverage their high marginal returns. Moreover, rather than making fragmented, low-level investments, fiscal strategies must ensure that funding for science popularization exceeds critical thresholds. This "critical mass" approach is essential to unlock the full potential of human capital and trigger qualitative leaps in regional innovation capacity.

Keywords

Science popularization personnel; Regional innovation; Threshold regression; Policy optimization

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1. Introduction

Innovation is not only the core driver of economic growth but also the fundamental pathway to resolving complex social issues and enhancing regional sustainable development capabilities. Against the backdrop of accelerating globalization and the knowledge economy, regional innovation capacity has become a key indicator for measuring a region's core competitiveness. As demonstrated by innovation ecosystem theory, scientific and technological innovation is not an isolated event of linear breakthroughs but rather relies on the synergistic coexistence of multidimensional factors such as institutional environments, talent reserves, and knowledge dissemination. The report of the 20th CPC National Congress explicitly outlined the strategic deployment to "strengthen national science popularization capacity building." The newly revised *Law of the People's Republic of China on the Popularization of Science and Technology* (2024) introduced a dedicated chapter on "science popularization personnel," legally defining the direction and requirements for building a science popularization talent pool[1]. It further stipulates that "science popularization is an integral part of the national innovation system and a foundational task for achieving innovative development," elevating the strategic importance of science popularization and the corresponding talent development to unprecedented heights.

By extensively disseminating scientific knowledge and scientific thinking, science popularization personnel promote knowledge spillover and play an indispensable role in enhancing public scientific literacy. This, in turn, provides impetus for stimulating regional innovation vitality and accelerating regional innovation processes. However, current policy implementation often exhibits a resource allocation bias that "prioritizes scientific research over science popularization." In 2022, spending on science popularization made by local governments nationwide accounted for only 1.54% of total science and technology expenditures, highlighting the disproportionately low allocation of resources to this field[2]. Furthermore, China faces severe regional imbalances in science popularization personnel. In 2022, Tianjin Municipality had 32.53 science popularization personnel per 10,000 people, while Heilongjiang Province had only 7.81[3]. Optimizing the scale and structure of science popularization personnel is urgently needed. Against this backdrop, a central research question emerges: Can investments in science popularization personnel enhance regional innovation capacity? If a positive correlation exists, does this impact vary across regions?

Existing research has predominantly focused on traditional innovation factors such as R&D investment and patent systems, while generally overlooking the potential driving role of non-R&D elements like science popularization in regional innovation (Pino and Ortega, 2018). Studies conducted from the science popularization perspective have also largely centered on social benefit indicators such as enhancing public scientific literacy, failing to delve into the quantitative relationship between science popularization investment and regional innovation (Ren and Zhai, 2014). Furthermore, existing research often relies on cross-sectional data or single-case analysis methods, making it difficult to examine the regional heterogeneity of science popularization investment (Fischhoff, 2018; Lin *et al*., 2019). This study aims to overcome these limitations by integrating panel data from 30 Chinese provincial level administrative regions spanning

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[1] *Law of the People's Republic of China on the Popularization of Science and Technology* (2024 Revision), adopted 25 Dec 2024 at the 13th Session of the Standing Committee of the 14th National People's Congress, Presidential Order No. 43 (PRC)

[2] *China Statistical Yearbook on Science and Technology 2023* (National Bureau of Statistics & Ministry of Science and Technology, China Statistics Press, 2023), 45.

[3] *China Science-Popularization Statistics 2022* (Ministry of Science and Technology, Department of Policy, Regulation & Innovation System, 2023), 12.

2013 to 2022 (Tibet Autonomous Region excluded due to data gaps). Employing fixed-effects models and threshold regression, we examine the impact of human resource investment in science popularization on regional innovation. In-depth research on these issues can not only optimize the allocation of science popularization resources and enhance the efficiency and effectiveness of such investments but also provide theoretical foundations for formulating differentiated regional policies. This, in turn, injects new momentum into the sustainable development of regional economies and societies.

2. Research Questions

The core of regional innovation systems lies in the creation, dissemination, and application of knowledge (Howells, 2002). Their efficient operation relies not only on the knowledge creation capabilities of high-level research entities but also on a supportive social environment that effectively absorbs, transforms, and applies innovative knowledge (Cohen and Levinthal, 1990; Zahra and George, 2002). Science communicators play an indispensable role in this process.

A region's overall human capital level forms the foundation of its innovation potential. Science communicators systematically enhance the foundational scientific literacy of both current and future regional labor forces through diverse outreach activities in science museums, schools, communities, and online platforms (Lin *et al*., 2019; Jensen and Buckley, 2014). Enhanced foundational scientific literacy reduces public barriers to understanding and accepting emerging technologies, thereby accelerating corporate adoption and application of innovations (Stilgoe *et al*., 2013). From a long-term perspective, high-quality science popularization can spark sustained interest in Science, Technology, Engineering, and Mathematics (STEM) fields among youth and encourage their engagement in these areas. This continuously supplies high-caliber talent to regional innovation systems, sustaining long-term regional competitiveness (DeJarnette, 2018).

Innovation often involves significant uncertainties and potential ethical controversies, and public skepticism or resistance toward innovation can hinder the commercialization of technologies (Gauchat, 2015). Science communicators can effectively enhance public understanding and trust in innovation (Von Schomberg, 2013), facilitating dialogue between researchers and the public and promoting Responsible Research and Innovation (RRI). Regions with high-quality, large-scale science popularization talent pools typically exhibit greater receptivity to new ideas and technologies, thereby fostering a more inclusive and supportive social environment for innovation.

It is crucial to recognize that the driving effect of investment in science popularization on regional innovation operates through two complementary logical pathways. On one hand, an increase in funding can significantly improve the working environment and supporting facilities for practitioners. Under the premise of a stable personnel scale, such capital deepening enhances the efficiency and professional quality of existing human capital, thereby increasing its marginal contribution to innovation through a "quality spillover" effect (Griliches, 1998). On the other hand, increased financial investment often leads directly to the expansion of the science communication workforce. By recruiting a more diverse range of professionals, a region can achieve broader knowledge coverage and deeper community penetration. This "scale effect" characterized by the sheer volume of human resources, works in tandem with the "quality effect" to determine the efficiency of knowledge absorption and the robustness of the regional innovation culture (Aurora and Teixeira, 2016). Furthermore, a well-funded environment not only optimizes internal processes but also attracts external high-level talent, creating a virtuous cycle of human capital accumulation (Holla *et al*., 2026).

In summary, science communicators provide foundational and long-term support for regional innovation development through three pathways: facilitating knowledge dissemination, enhancing citizen scientific literacy, and cultivating regional innovation culture. The scale and quality of these efforts significantly influence regional knowledge absorption efficiency, talent supply systems, and cultural environments. Based on this, this paper proposes the first research question:

RQ1: Investment in science popularization human capital positively promotes regional innovation capacity; greater numbers of science communicators correlate with stronger regional innovation capacity.

Science popularization has the typical attribute of a public good, and its significant positive social external effects often prevent the market mechanism from fully providing such services (Stiglitz and Rosengard, 2015; Kaul *et al*., 1999). This situation leads to the government occupying a dominant position in the construction of science popularization infrastructure and the cultivation of talent teams (Mazzucato, 2016; Bozeman and Youtie, 2017). However, the investment of public funds does not simply translate into innovation performance through a linear path; instead, it follows a nonlinear threshold effect mechanism (Hansen, 2000; Liu *et al*., 2025). According to the threshold regression theory, when an explanatory variable does not reach a specific critical value, its impact on the explained variable may be negligible; but once it crosses this threshold, the nature and intensity of this impact will undergo a structural change (Wang, 2015; Getzner, 2017). While in their paper, Shapiro and Varian argues that due to the "critical scale theory" and "network externality" factors, there will be a structural transformation (2013).

During the stage when public fund investment is below the critical threshold, science popularization activities often fall into the "survival maintenance" predicament. Due to the lack of support from economies of scale, limited funds are mainly used to cover short-term labor costs and basic operating expenses, making it difficult to achieve substantive capital accumulation (Jensen and Buckley, 2014). According to the resource dependence theory, in this stage, human capital in the field of science popularization is severely limited by material conditions, leading to dispersed activities and reduced activity frequency (Pfeffer and Salancik, 2003; Hillman *et al*., 2009). Even if the investment in human capital is increased, the marginal output remains extremely low (Simis *et al*., 2016). This "lock-in effect" caused by resource scarcity inhibits the spillover effect of science popularization on regional innovation, resulting in statistically insignificant or weakly influential outcomes (Hall and Lerner, 2010).

Once public fund investment exceeds a specific critical threshold, the system undergoes a qualitative transformation. Infrastructure investment is inseparable, and core infrastructure such as large science museums require high fixed costs, and can only be built when funds accumulate to a certain level (Falk and Dierking, 2013). Once this threshold is crossed, advanced infrastructure becomes an enabling technology, greatly releasing the productivity of existing human capital and transforming science popularization from a purely labor-intensive model to a technology-driven model (Agrawal *et al*., 2014; Gascoigne *et al*., 2020). In addition to improving the working environment, the investment beyond this threshold will also trigger key "scale aggregation effects" and the optimization of the talent structure. Adequate funds not only support larger teams but also attract high-level interdisciplinary experts, thus forming the necessary scale for knowledge spillover. This expansion of talent scale and structural upgrading triggered by funds will generate significant network external effects (Katz and Shapiro, 1985). As the nodes in the communication network increase, the penetration and influence of scientific culture grow exponentially rather than linearly (Metcalfe, 1998; Cooke, 1992). At this stage, human capital in science popularization is no longer an isolated factor but has a deep resonance with the regional innovation system through modern platforms and close collaboration networks.

In conclusion, when public funds reach the threshold, by eliminating the rigid limitations of infrastructure and activating the network effect of talent aggregation, it triggers such a structural change: The marginal return of science popularization human capital driving regional innovation shows an increasing characteristic (Romer, 1990; Lucas, 1988). Based on this, the second research question of this study is proposed:

RQ2: Public fund investment in human capital for science popularization shows significant threshold characteristics in regulating the promoting effect of science popularization human capital on regional innovation.

China exhibits significant regional development imbalances, with substantial disparities in economic development levels, industrial structures, and educational resources between the eastern, central, and western regions (Wei, 2007). These differences imply that the same policies may yield markedly divergent outcomes across regions, reflecting the "regional heterogeneity" of policy effects (Rodríguez-Pose and Crescenzi, 2008). The eastern regions typically possess stronger economic foundations, host universities and research institutions with outstanding research capabilities, and maintain more comprehensive talent and innovation systems (Wan *et al*., 2024; Fischer *et al*., 2024). In such environments, innovation relies more heavily on cutting-edge technological advances and the concentration of high-caliber talent. While investments in science popularization retain value, their marginal contribution to overall innovation capacity may be weaker than large-scale R&D investments. Science popularization primarily serves to maintain and optimize the innovation system.

In contrast, China's western regions face relatively weak science popularization resources and innovation foundations. These areas commonly grapple with practical challenges such as uneven distribution of educational resources and low levels of public scientific literacy (Li, 2009; Crescenzi and Rodríguez-Pose, 2017). Against this backdrop, the strategic value of investing in science popularization human capital becomes prominent, potentially generating stronger "pull effects." With relatively underdeveloped economies and limited funding for science popularization, human resources in this field emerge as a critical factor influencing regional innovation. By disseminating scientific knowledge and concepts, science popularization human capital can effectively dismantle cultural barriers hindering the spread of science and technology, creating essential social conditions for introducing external knowledge and technologies (Abramovitz, 1986; Keller, 2004). Beyond disseminating scientific knowledge, science communicators also shoulder the missions of cultivating innovative talent and facilitating technology transfer. This multifaceted role enhances the marginal benefits of human capital investment under resource constraints. Given the chronic underinvestment in science popularization personnel in the western regions of China, additional human capital investment can overcome critical bottlenecks and accelerate regional innovation. Thus, the same investments in science popularization human capital may yield greater incremental innovation returns in such regions. Based on this, this paper proposes a third research question:

RQ3: The impact of human capital investment in science popularization on regional innovation capacity exhibits regional heterogeneity in China, with the strongest pull effect observed in the western regions of the country.

3. Research Design

3.1. Data sources

The data utilized in this article is sourced from the *China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Popular Science Statistical Yearbook, China Education Statistical Yearbook,* and *China Regional Innovation Capability Comprehensive Evaluation Report* for each period from 2013 to

2022. Therefore, the research subjects are the 30 provinces, municipalities, and autonomous regions in the Chinese mainland. Additionally, the regions are divided into the eastern, central, and western regions according to the classification method of the statistical yearbooks. The eastern region includes 11 provinces and municipalities such as Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes 8 provinces such as Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes 11 provinces, autonomous regions, and municipalities such as Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

3.2. Variable description

(1) Explained variable

Regional Innovation Capacity: Regional innovation capacity refers to a region's comprehensive ability to achieve technological advancement and economic value creation through technological R&D, achievement transformation, and resource allocation. It serves as the core engine driving economic growth (Romer, 1990; Cooke, 1992), serving as a measure of regional efficiency in knowledge production, technology diffusion, and commercial application. This study employs the "Comprehensive Regional Innovation Capacity Index" published in the *China Regional Innovation Capacity Evaluation Report* as the metric.

(2) Explanatory variable

Science popularization Human Resource Input: Science popularization personnel serve as carriers of knowledge dissemination, and their scale reflects a region's human resource reserves for science popularization. Unlike the large-scale workforce in scientific research, the number of full-time science popularization practitioners is limited, particularly in grassroots or underdeveloped areas where part-time personnel significantly outnumber full-time staff. Part-time science popularization workers (such as university faculty, volunteers from research institutions, and retired experts) play a crucial role in science popularization. Relying solely on full-time personnel statistics would underestimate the actual scale of human resource investment. Therefore, this paper measures science popularization human resource investment using both full-time and part-time personnel counts, with data sourced from the China science popularization Statistics.

(3) Control variables

Drawing on existing research, this paper selects control variables correlated with regional innovation capacity. Research funding is measured by the intensity of research and experimental development (R&D) expenditure. Industrial agglomeration is assessed using the number of high-tech enterprises (ENT). Economic structure is measured by the growth rate of tertiary sector GDP (TER). Educational attainment is measured by the proportion of the population with higher education (EDU) (Gennaioli *et al.*, 2013; Aarstad and Kvitastein, 2020; Wang *et al.*, 2022). Data sources include the China Statistical Yearbook, *China Science and Technology Statistical Yearbook*, and *China Education Statistical Yearbook*.

(4) Threshold variable

Science popularization Funding: science popularization funding serves as the core variable underpinning the comprehensive development of science outreach. It not only provides foundational support for building science popularization talent pools but also plays a decisive role in infrastructure development and activity coverage. The public good nature of science popularization inherently limits market actors' motivation to invest in this field, making government allocations the primary source of funding. Government funding accurately reflects policy makers' commitment to science popularization and mitigates measurement biases caused by market fluctuations influenced by economic cycles and operational volatility. Furthermore, since science popularization funding allocations are independently managed by local governments, utilizing government grant data enables precise identification of regional disparities in science resource distribution, providing a basis for optimizing fiscal transfer payment mechanisms. Therefore, this paper employs government-allocated science popularization funding as the metric for measuring investment, drawing data from China science popularization Statistics and publicly available reports from provincial science and technology departments.

3.3. Model specification

To examine the relationship between science popularization investment and regional innovation capacity, the following baseline regression model is proposed:

$$RII_{i,t}=\beta_0+\beta_1 STFF_{i,t}+\gamma_i X_i+\sum Region+\sum Year+\epsilon_{i,t} \quad (1)$$

where the dependent variable $RII_{i,t}$ represents the regional innovation capability composite index ($RII_{i,t}$ denotes the composite innovation index for region i in year t); $STFF_{i,t}$ represents the explanatory variables; β0 denotes the constant term; $X_{i,t}$ comprises other control variables, namely R&D expenditure intensity, number of high-tech enterprises, tertiary sector GDP growth rate, and proportion of higher education population. $\sum Region$ and $\sum Year$ denote industry fixed effects and time fixed effects, respectively; $\epsilon_{i,t}$ represents the residual term; β_i denotes the regression coefficient for explanatory variables. A positive coefficient indicates that investment in science popularization personnel positively impacts regional innovation capacity, while a negative coefficient suggests a negative effect; γ_i represents the regression coefficients for each control variable. Equation (1) corresponds to RQ 1 above.

4. Analysis and Results

4.1. Descriptive statistics

Table 1
Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
RII	300	29.078	10.817	15.78	65.49
STPP	300	6.331	3.619	0.779	19.22
RDI	300	1.841	1.156	0.475	6.37
ENT	300	1155.577	1734.592	28	10106
EDU	300	0.16	0.078	0.074	0.489
TER	300	0.074	0.031	-0.011	0.126
STPF	300	2.212	2.269	0.129	12.625

Table 1 presents descriptive statistics after tail trimming. The table reveals that the mean of the regional innovation capability composite index is 29.078, with a range of 49.71, indicating substantial disparities in innovation levels across regions. The maximum value for science popularization personnel investment is 19.22, while the minimum is only 0.779, indicating substantial regional disparities in this investment; the standard deviation for science popularization funding is 2.269, close to the mean of 2.212, with a minimum of 0.129, suggesting severe funding shortages in some regions.

4.2. Benchmark regression analysis

Table 2
The effect of science popularization human resource input on regional innovation capacity: Baseline results.

Regression Results					
Variable	RII				
	(1)	(2)	(3)	(4)	(5)
STPP	0.323*** *(4.22)*	0.274*** *(3.83)*	0.256*** *(3.65)*	0.256*** *(3.64)*	0.254*** *(3.61)*
RDI		3.588*** *(6.52)*	2.678*** *(4.50)*	2.682*** *(4.49)*	2.73*** *(4.51)*
ENT			0.001*** *(3.57)*	0.001*** *(3.51)*	0.001*** *(3.49)*
EDU				1.110 *(0.14)*	0.891 *(0.11)*
TER					-5.052 *(-0.55)*
Constant Term	27.596*** *(43.29)*	21.896*** *(20.74)*	22.571*** *(21.50)*	22.425*** *(15.30)*	22.884*** *(13.52)*
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.180	0.670	0.860	0.861	0.860
Sample Size	300	300	300	300	300

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10% respectively; t-values are in parentheses.

The benchmark regression results are presented in Table 2 As shown in Column (1) above, without considering other control variables, science popularization personnel investment positively impacts regional innovation and is statistically significant at the 1% level. This indicates that science popularization personnel investment can effectively promote regional innovation development. Throughout the process of progressively adding control variables, the STPP coefficient remains consistently and significantly positive, demonstrating that science popularization personnel investment has a robust and positive effect on regional innovation capacity.

4.3. Robustness tests

To ensure the reliability of the benchmark regression results, robustness tests were conducted by excluding special samples, altering the sample range, and modifying the measurement method of the explanatory variable. Additionally, lagged science popularization manpower input was used as an instrumental variable to address potential endogeneity issues. After accounting for endogeneity and conducting a series of robustness tests, the conclusions remained valid, indicating that the benchmark regression results possess good robustness.

Table 3
Robustness checks.

Robustness Test Results			
	Comprehensive Index of Regional Innovation		
Variable	Exclusion of Special Samples Four Directly Administered Municipalities	Replacement of Sample Scope Exclusion of Data for 2013 and 2014	Endogeneity Analysis Instrumental Variable Method
Human Resource Input	0.39*** *(4.85)*	0.337*** *(3.04)*	1.044** *(2.40)*
Constant	21.881*** *(13.07)*	22.478*** *(9.67)*	-
Control Variables	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.461	0.399	0.141
Sample Size	300	300	270

Note: ***, **, and * indicate significance levels of 1%, 5%, and 10% respectively; t-values are in parentheses.

4.3.1. Exclusion of special samples

Beijing, Shanghai, Tianjin, and Chongqing, as China's four municipalities directly administered by the central government, possess unique characteristics in administrative status and resource allocation that may affect the model's generalizability. Therefore, their sample data were excluded to verify model robustness. The validation results in Table 3.3 show that the regression coefficient for science popularization human capital investment increased from 0.254 in the benchmark model to 0.39, significant at the 1% level. This indicates that in non-municipal samples, the marginal effect of science popularization human capital investment on regional innovation is higher. This may stem from municipalities typically possessing mature innovation ecosystems where innovation activities rely less on science popularization personnel, whereas other provinces with relatively weaker innovation foundations exhibit more pronounced marginal effects from science popularization personnel investment.

4.3.2. Changing the sample scope

Excluding data from 2013 and 2014, we again tested model robustness by changing the sample scope. As shown in the table above, the coefficient for science popularization personnel investment increased from 0.254 in the baseline model to 0.337, significant at the 1% level. This reaffirms that science popularization personnel investment has a significant positive impact on regional innovation.

4.3.3. Endogeneity analysis

The empirical regression examining the impact of science popularization manpower investment on regional innovation may encounter reverse causality issues—regions with higher innovation capabilities may exhibit greater science popularization manpower investment. To address potential endogeneity, this study employs lagged science popularization manpower investment (*lag1_STPP*) as an instrumental variable and utilizes panel two-stage least squares (2SLS) estimation. The first-stage instrumental variable estimation yielded a positive and significant coefficient. The Kleibergen-Paap rk LM and Cragg-Donald

Wald F statistics confirmed that the instrumental variable (*lag1_STPP*) passed the unidentifiability and weak instrument tests, establishing its validity. In the second stage, with the instrumental variable incorporated, the coefficient for science popularization personnel investment remained significantly positive, indicating that the empirical findings remained robust and reliable after addressing endogeneity concerns.

4.4. Heterogeneity test

Table 4
Heterogeneity analysis.

Regression Results by Eastern, Central, and Western Regions			
Variable	Comprehensive Index of Regional Innovation		
	Eastern	Central	Western
Human Resource Input	0.266** (2.63)	-0.341** (-2.18)	0.378*** (2.86)
Constant	20.467*** (5.17)	30.409*** (14.60)	16.318*** (6.70)
Control Variables	Yes	Yes	Yes
Regional Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R^2	0.544	0.3	0.757
Sample Size	100	120	80

To examine the heterogeneity of the impact of science popularization human resource investment on regional innovation across different areas, the 30 provinces in the study sample were categorized into the eastern, central, and western regions based on the National Bureau of Statistics' regional classification. The regression results in Table 4 reveal significant heterogeneity in the influence of science popularization human resource investment on regional innovation across China's eastern, central, and western regions. In the western region, the regression coefficient for science popularization human resources is positive and statistically significant at the 1% level, indicating a pronounced "leverage effect" of such investments in this area. Given the relatively underdeveloped educational resources and weaker innovation foundations in the western region, science popularization activities partially compensate for educational shortcomings, lower barriers to technology adoption, and stimulate innovation development. In the eastern region, the regression coefficient for science popularization personnel investment remains positive and significant at the 5% level. This may be attributed to the eastern region's established mature innovation networks, where abundant innovation resources dilute the marginal utility of science popularization personnel. The regression coefficient for science popularization personnel investment in the central region exhibits an anomaly, being negative. This likely stems from the central region's large scale of science popularization personnel coupled with deficiencies in the critical factor of science popularization quality. Moreover, traditional manufacturing dominates the central region, where local enterprises exhibit relatively low demand for cutting-edge technologies. This mismatch between science popularization content and practical needs prevents the full utilization of science popularization resources. Additionally, the central region suffers from severe talent drain, with a significant number of science and technology professionals trained in its universities migrating to the east. This exodus creates a shortage of innovation drivers, making it difficult for science popularization personnel investments to compensate for the core R&D talent gap.

4.5. Threshold regression results

To examine whether a nonlinear relationship exists between science popularization investment and regional innovation, this study employs the panel threshold regression model proposed by Hansen (1999). Using science popularization funding as the threshold variable, the model was estimated using Stata MP 18 software. Bootstrap sampling was conducted 300 times to test for the presence of threshold effects. The model specification is presented in (2).

$$RII_{i,t} = \beta_0+\beta_1 \text{STPP} \cdot 1(\text{STPF} \leq \gamma_1)+\beta_2 \text{STPP} \cdot 1(\gamma 1<\text{STPF} \leq \gamma_2) +\beta_3 \text{STPP} \cdot 1(\text{STPF} >\gamma 2)+a_i X_{i,t}+\epsilon_{i,t} \quad (2)$$

where $1(\cdot)$ denotes the indicator function and X includes control variables such as R&D funding intensity, number of high-tech enterprises, tertiary industry GDP growth rate, and proportion of higher education population.

The single-threshold test yielded an F-value of 18.58 (P=0.02), while the dual-threshold test produced an F-value of 15.41 (P=0.037). Both results significantly rejected the null hypothesis of “no threshold,” indicating the presence of dual nonlinear breakpoints. The triple-threshold test failed to pass. Specific threshold values and parameter estimates are shown in the table below.

Table 5
Threshold values and parameter estimation.

Parameter	Variable	Estimate	t-value	95% Confidence Interval
β_1	STPF≤0.459	-0.618	-2.89	[-1.04,-0.197]
β_2	0.459<STPF≤4.205	0.213**	2.81	[0.063,0.362]
β_3	STPF>4.205	0.414**	5.59	[0.268,0.559]

Table 5 reveals two threshold values for science popularization funding: 0.459 and 4.205. This study defines funding levels below 0.459 as low, between 0.459 and 4.205 as medium, and above 4.205 as high. The fitted coefficients β_1, β_2, and β_3 reveal that different levels of science popularization funding exert significantly divergent effects on regional innovation.

When science popularization funding (STPF) falls below the first threshold (0.459), it exerts a significant negative impact on regional innovation (β_1=-0.618). This counterintuitive phenomenon may arise because insufficient funding severely hampers the work of science popularization personnel. Limited resources can only sustain one-off or short-term low-cost activities, restricting outreach coverage and preventing science popularization personnel from effectively fulfilling their roles.

When STPF exceeds the first threshold (0.459 < STPF ≤ 4.205), the coefficient turns positive but exhibits low intensity (β_2 = 0.213). This may occur because increased funding secures basic science popularization infrastructure and activities, gradually builds regional science networks, and accelerates knowledge dissemination. However, funding constraints hinder support for high-cost projects, limiting activities primarily to basic science knowledge dissemination that often fails to align with industrial innovation needs. Furthermore, the finite nature of science outreach funds fails to attract more specialized talent, ultimately constraining both the breadth and depth of outreach coverage.

When funding surpasses the second threshold (STPF > 4.205), the coefficient significantly increases to 0.414—roughly double the mid-level funding range. This may occur because high-funding regions can assemble specialized science popularization teams, such as retired experts from research institutions, to enhance knowledge dissemination efficiency. Sufficient funding also supports high-end science outreach projects, fosters mature science popularization ecosystems, and creates synergies with industry and R&D sectors.

Research regions were categorized based on funding threshold intervals, yielding the grouping results shown in the table below. Table 6 indicates that all regions surpassed the first threshold. Beijing, Shanghai, Jiangsu, and Guangdong crossed the second threshold, placing them in the high-funding group, while most regions fell into the medium-funding group.

Table 6
Grouping Table of Regions by Human Resource Input in science popularization (Classified by science popularization Fund Input).

Group	Threshold Variable Value	Provinces Included in Each Group	Sample Size
Low Fund Input	STPF≤0.459	-	0
Medium Fund Input	0.459<STPF≤4.205	Tianjin, Hebei, Liaoning, Zhejiang, Fujian, Shandong, Hainan, Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	26
High Fund Input	STPF>4.205	Beijing, Shanghai, Jiangsu, Guangdong	4

5. Discussion and Conclusion

5.1. Research findings

(1) Investment in science popularization personnel significantly enhances regional innovation capacity.

The findings indicate that investment in science popularization personnel substantially boosts regional innovation capacity. When controlling for other variables, this investment exerts a positive influence on regional innovation, achieving statistical significance at the 1% level. Throughout the stepwise introduction of control variables, the regression coefficient for science and technology popularization personnel (STPP) remained consistently and significantly positive. After conducting a series of robustness tests—including excluding outlier samples, adjusting sample ranges, and modifying explanatory variable measurement methods—along with addressing endogeneity issues, the regression coefficient remained significantly positive. This confirms Research Question 1 (RQ1). From the perspective of Human Capital Theory, science popularization personnel act as specialized intermediaries who reduce the cognitive cost of knowledge acquisition for the public. By enhancing the general population's scientific literacy, they increase the region's aggregate "Absorptive Capacity" (Cohen and Levinthal, 1990), thereby facilitating the diffusion and commercialization of new technologies.

(2) Significant regional heterogeneity, with the strongest marginal effect in the western region.

As indicated by the aforementioned regional regression results, the impact of science popularization human resource investment on regional innovation exhibits significant spatial heterogeneity. Among regions, the western region demonstrates the most pronounced driving effect of science popularization human resource investment on regional innovation, with its regression coefficient being significantly positive at the 1% level. This may stem from the relatively weaker educational resources and insufficient innovation foundations in the western regions, where science outreach activities compensate for educational gaps and lower technological adoption barriers to drive innovation. Science outreach personnel in eastern regions also exert a positive and statistically significant (at the 5% level) influence on regional innovation. This likely arises because the eastern regions have established mature innovation networks, where abundant innovation resources partially dilute the marginal utility of science outreach personnel. In contrast, the regression coefficient for science popularization personnel investment in the central regions is negative. This may stem from factors such as the continuous expansion of science popularization personnel in central regions without corresponding improvements in quality, the disconnection between their work and actual industrial needs, and severe talent loss.

(3) Science popularization funding exhibits a nonlinear threshold effect.

When funding exceeds the second threshold, the positive effect significantly strengthens. This validates the "Critical Mass" hypothesis within innovation ecosystems. The finding suggests that science popularization is not a linear input-output process but relies on "Network Externalities." Only when the density of funding and talent exceeds a critical level does the system shift from isolated knowledge transmission to a self-reinforcing innovation culture. The threshold regression model reveals that government funding for science popularization (STPF) exhibits a significant dual threshold effect on regional innovation (threshold values 0.459 and 4.205). When funding levels fall below 0.459, it exerts a significant negative impact on regional innovation (β_1 = -0.618). This may occur because insufficient funding only sustains low-cost outreach activities, failing to fully leverage the potential of science popularization personnel. After crossing the first threshold (0.459 < STPF ≤ 4.205), the impact of funding on innovation becomes positive but relatively weak (β_2 = 0.213). This may occur because increased funding supports basic science popularization infrastructure and activities, yet constrained by scale, high-cost projects remain difficult to implement and insufficient to attract specialized science popularization talent. When funding exceeds the second threshold (STPF > 4.205), the positive effect significantly strengthens (β_3 = 0.414). Regions with high funding can then attract specialized science popularization teams, support high-end science popularization projects, and build a mature science popularization ecosystem, ultimately achieving synergistic development between science popularization, industry, and R&D. This finding corresponds to Research Question RQ3, indicating that science popularization funding must surpass specific thresholds to effectively unleash its innovation-driving potential. Grouping the study regions by funding levels reveals that all regions surpassed the first threshold. However, most regions fall into the medium funding category, with only Beijing, Shanghai, Jiangsu, and Guangdong crossing the second threshold into the high funding category. This imbalance may widen innovation gaps between regions, particularly as the central and western regions struggle to overcome innovation bottlenecks due to funding constraints.

5.2. Discussion

The first major theoretical contribution of this study is the expansion of Absorptive Capacity Theory beyond its traditional R&D-centric focus. Conventional models typically emphasize R&D investment as the primary mechanism for recognizing and assimilating new information. However, our findings suggest that science popularization personnel serve as a critical social and cognitive bridge. By disseminating scientific knowledge to a broader "knowledge receiver" base, these personnel facilitate the conversion of external knowledge spillovers into tangible innovation outputs. This discovery modifies traditional theory by highlighting a dissemination-based mechanism that complements internal R&D, thereby providing a more holistic understanding of regional knowledge utilization.

The second contribution lies in the application of Network Externality Theory and Critical Mass Theory to the field of science communication. Our identification of the double-threshold effect contradicts simple linear input-output models and suggests that science popularization operates through a network logic. The funding threshold acts as the "critical scale" necessary to trigger a "scale agglomeration effect," allowing dispersed practitioners to form a cohesive, synergistic network. Only after crossing this threshold does the system move away from mere labor accumulation toward a systemic environment where positive externalities and self-reinforcing innovation cultures can flourish.

Although this study provides reliable empirical evidence, it is necessary to acknowledge that there are certain limitations in the measurement of variables and the scope. These limitations should serve as a reference for future research. Regarding the measurement of human capital, this study mainly uses the number of full-time and part-time science popularization personnel as the main indicator of input. Although this method can reflect the size of the labor force, it fails to take into account the qualitative aspects of human capital, such as the educational background, professional skills, or professional training duration of the personnel. Future research should attempt to construct a weighted index that takes into account factors such as the proportion of personnel with advanced degrees or professional certificates, in order to provide a more accurate assessment of the efficiency of human capital.

5.3. Policy recommendations

(1) Increase investment in science popularization personnel and optimize the science popularization workforce.

All regions should further enhance investment in science popularization, establish sound career development mechanisms for science popularization personnel, and attract outstanding talent to the field through measures such as improving compensation packages, enhancing work environments, and providing career advancement opportunities. To optimize the science popularization workforce, training should be strengthened for practitioners to enhance their scientific knowledge and communication skills, ensuring the quality and effectiveness of outreach activities while preventing resource wastage. Universities and research institutions should be encouraged to establish science popularization-related majors and courses to cultivate specialized talent, thereby improving workforce development.

Furthermore, given the regional heterogeneity in how human resource investment in science popularization drives innovation, differentiated strategies can maximize human potential. The western regions should expand their science popularization workforce, develop more attractive talent programs to engage scientists, university faculty, and others in grassroots outreach, promote integration with education, and leverage digital platforms and new media to bridge educational resource gaps. The eastern regions should optimize human resource structures, advance the professional transformation of science popularization personnel, guide research institutions and high-tech enterprises to engage in science popularization, form cross-disciplinary expert teams, enhance the precision of science popularization services, and further strengthen science popularization quality. The central regions urgently need to improve science popularization quality and talent retention capabilities. They should focus on the science popularization needs of innovation entities, establish demand-driven mechanisms for selecting science popularization content, and improve talent incentive mechanisms to curb the outflow of scientific and technological talent.

(2) Rationally allocate science popularization funding to overcome threshold effects.

Based on the average science popularization funding over the past decade, the 30 provincial-level administrative regions in the studied sample were categorized. Results indicate that only four provinces—Beijing, Shanghai, Guangdong, and Jiangsu—are high-funding regions, while most others fall into the medium-funding category. Regions should rationally allocate science popularization funding based on local conditions to overcome threshold effects and effectively promote regional innovation. Moderate-investment regions should enhance funding efficiency by establishing feasible performance evaluation systems for science popularization projects. With limited budgets, priority should be given to sustainable, high-conversion-rate initiatives while maximizing human resource utilization. Regions in the high-funding category, such as Beijing, Shanghai, Jiangsu, and Guangdong, should actively explore new models and mechanisms for synergistic development between science popularization funding and industrial innovation. Building upon existing strengths, they should further develop and refine collaborative science popularization ecosystems and explore new development pathways.

(3) Establish regional coordination mechanisms to narrow regional innovation gaps.

The impact of human resource investment in science popularization on regional innovation exhibits significant regional heterogeneity. Concrete measures should be taken to advance regional coordination and reduce innovation disparities. The economically developed eastern regions, equipped with comprehensive innovation ecosystems and abundant science popularization resources, should leverage their strengths to enhance collaboration and interaction with the central and western regions. Regularized mechanisms for science popularization talent exchange can be established, organizing experts and outstanding practitioners from the eastern regions to conduct training, lectures, and to give guidance in the central and western regions, thereby disseminating advanced science popularization concepts and methodologies. Additionally, the shared utilization of science popularization resources can be promoted by establishing digital platforms to open high-quality science popularization courses, materials, and exhibitions to the central and western regions, facilitating more balanced distribution of resources. The central and western regions should learn from the advanced popular science experiences and development models of the eastern regions. They should formulate efficient and feasible popular science development strategies tailored to their regional characteristics and development needs. Particularly in the central regions, where the effectiveness of popular science personnel deployment is suboptimal, it is necessary to thoroughly analyze the underlying causes and implement targeted measures. To address the mismatch between the scale and quality of science popularization personnel, efforts should focus on strengthening the training and education to enhance their professional competence and operational skills. The direction and core priorities of science popularization work should be optimized to align with industrial demands, preventing content from becoming detached from practical realities. Governments should introduce talent return policies offering preferential measures and favorable development environments to attract outflowing scientific and technological talents back to their regions. This will create sufficient conditions for nurturing local innovation entities and advancing science popularization initiatives.

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Conflicts of Interest

The authors declare no conflict of interest.

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