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Fiscal science and technology expenditure and the spatial convergence of regional innovation efficiency: evidence from China's province-level data

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ABSTRACT

Narrowing the gap in regional innovation efficiency is conducive to the coordinated development of regional economies. Fiscal science and technology (S&T) expenditure is the government's primary means of supporting regional innovation. It also plays an essential role in improving the efficiency of regional innovation. This study constructs a spatial convergence economic model based on a dynamic perspective. It also examines the relationship between fiscal S&T expenditure and spatial convergence of regional innovation efficiency. China's regional innovation efficiency shows a trend of conditional β-convergence. Fiscal S&T expenditure positively affects the spatial convergence of regional innovation efficiency and has an inverted U-shaped, nonlinear relationship as a whole. The transmission mechanism test revealed that the cross-regional flow of research and development (R&D) personnel can enhance this positive effect, and the role of R&D capital is not significant.

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1. Introduction

China's economic development has always been the focus of researchers' attention. Since China adopted economic reforms and opened up, it has attained remarkable achievements in economic development. However, the government's excessive focus on the speed of economic growth led to huge gaps in regional economic development (Zhou et al., 2020). This is mainly attributed to differences in regional innovation, which is not a closed system but one replete with element flow and exchange. Capital, technology, and labour are the key elements that affect innovation. Further, cross-regional flow strengthens the spatial correlation of innovation in regions. If the input innovation resources cannot be effectively used and transformed in a region, some innovation elements will flow from this region to other areas. Additionally, if the innovation-related achievements in one area do not match its economic structure,

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the achievements will also flow to other areas. In a market economy, low regional innovation efficiency reduces the attractiveness of a region to innovation resources. This not only leads to the loss of regional innovation elements, but also widens the regional gap in innovation efficiency. At the same time, innovation is a crucial driver of regional economic growth (Grillitsch et al., 2019). The gap in innovation efficiency has a restraining effect on the balanced development of regional economy. Therefore, the key to narrowing the gap in regional economic development is narrowing the gap in regional innovation efficiency and promoting its spatial convergence (Ferreira, 2020; Falck et al., 2019; Manzano & Gutiérrez, 2019).

Technological innovation entails long-term, high-risk, positive externalities, which makes the supply of innovative elements lower than the equilibrium level of the market. It is difficult for the market to correct the failure of the allocation of innovation resources, which also highlights the irreplaceability of government investment in technological innovation activities. A direct way for the government to participate in innovation is through fiscal S&T expenditure to provide funds for technological innovation-related activities. The scope of fiscal S&T expenditure includes S&T management, basic research, applied research, technology research and development, technology conditions and services, social sciences, S&T popularisation, and technology exchanges and cooperation. Fiscal S&T expenditure entails high efficiency and targeting. On the surface, it plays a positive role in guiding the flow of innovation elements, making up for market deficiencies, and improving regional innovation efficiency. However, with the deepening of technological innovation, it has continued to increase. Further, fiscal expenditure that deviates from the market has not achieved significant technological progress. The government's ineffective investment has greatly affected the coordinated development of regional innovation (Květoň & Horák, 2018; Zúñiga-Vicente et al., 2014). Additionally, due to the large gap between the fiscal revenues of various provinces in China, especially in the eastern and western regions, there is a significant gap in the fiscal S&T expenditure of various provinces. Under such circumstances, in the process of regional coordinated development, what impact does fiscal S&T expenditure have on regional innovation efficiency? What is its mechanism of influence? This study discusses these core issues. Solving these problems is of practical significance for clarifying the role of fiscal policy in regional innovation efficiency and narrowing the gap regarding the same.

Considering the characteristics of the possible spatial correlation of regional innovation efficiency, this study uses the data envelopment analysis (DEA-Malmquist) method to measure the innovation efficiency of 30 provinces in China, and combines the convergence model and the spatial econometric model to study the spatial effect of fiscal S&T expenditure on regional innovation convergence. Secondly, we also constructed a mediation effect model to analyse the influence mechanism. The R&D personnel element flow and the capital element flow are the main paths for fiscal S&T expenditure to affect the convergence of regional innovation. In addition, to ensure the scientificity of the research results, some robustness tests were also carried out in this study. Finally, the policy implications are put forward to provide suggestions for the improvement of regional innovation efficiency.

The marginal contributions of this study are as follows. First, from the perspective of public finance, we analyse the dynamic relationship between fiscal S&T

expenditure and the spatial convergence of regional innovation efficiency and demonstrate its influence mechanism. It is based on the analysis of regional innovation trends and is more in line with the needs of social development. Second, in terms of model construction, we incorporate spatial factors into the traditional convergence model to construct a spatial autoregressive convergence model (SAR) and a spatial error convergence model (SEM), which is conducive to improving the accuracy of the research results. Third, we use the DEA-Malmquist method to measure the regional innovation efficiency of China's provinces from 2012 to 2018 and use this to study the convergence of regional innovation efficiency, which is different from research that only uses the number of patents to express innovation efficiency.

The remainder of this study is organised as follows. The second part is the literature review. The third part is the theoretical analysis and research hypothesis. The fourth part is the empirical design. The fifth part presents the result analysis. Finally, the conclusions and policy implications are presented.

2. Literature review

Fiscal S&T expenditure is an essential driving factor of regional innovation. It not only has individual effects, but also spatial effects (Montmartin & Herrera, 2015). Existing research has discussed the relationship between fiscal S&T expenditure and regional innovation, which is generally divided into three categories. First, fiscal S&T expenditure can have a significant driving effect on regional innovation. It increases R&D investment, solves the problem of market failure caused by non-proprietary investment, and reduces the risk and cost of enterprise technology investment. Simultaneously, fiscal S&T expenditure has prominent signal characteristics. It can alleviate the dilemma of information asymmetry between innovation entities and market elements, guide market elements into the field of technological innovation, and improve regional innovation efficiency (Montmartin & Massard, 2015). Second, fiscal S&T expenditure inhibits regional innovation efficiency. With the increase in fiscal S&T expenditure, the supply and demand of innovation elements in the market have changed. The increase in element prices caused by changes in demand increase the cost of innovation. This in turn has a crowding-out effect on the innovation of enterprises in the region (Guo et al., 2016). Additionally, the allocation of innovative resources based on government preferences may lead to misallocation of resources, which may easily induce rent-seeking behaviours of government and enterprises and make technological innovation fall into a low-level equilibrium and regulatory trap (Li et al., 2017). Third, there is an inverted U-shaped, nonlinear relationship between fiscal S&T expenditure and regional innovation. Fiscal S&T expenditure has threshold effects due to changes in the scale of fiscal expenditure, enterprise heterogeneity, institutional constraints, and intellectual property protection (Gao et al., 2020; Li et al., 2021).

There are few existing studies on the spatial effects of regional innovation. Min et al. (2020) analysed the spatial distribution characteristics and autocorrelation of Chinese government R&D expenditure. He found that the government's R&D expenditure showed an unbalanced distribution of spatial characteristics. Further, competition for government expenditure on S&T accelerated the spatial flow and convergence of R&D factors. At the same time, Patrick and Hussler (2005) believed that under the influence of the heterogeneity of factors, such as market environment, infrastructure, and government capabilities, the accumulation of innovation resources has formed an excellent innovation cycle system. However, it also triggers the Matthew effect of regional innovation and increases the gap in regional innovation. Smith and Song (2004) believed that regional innovation has a diffusion effect, and market integration promotes the flow of innovative elements, technology exchanges, and regional cooperation. Regions with a high level of innovation will drive the development of regions with a low level of innovation wherein regional innovation tends to converge.

Existing research has explored the impact of fiscal S&T expenditure on regional innovation and contributed in the following ways. First, it affirmed the relationship between fiscal S&T expenditure and regional innovation. However, there is no specific conclusion or precise transmission mechanism (Chen et al., 2020; Yang et al., 2021). Second, it focussed on analysing the individual effects of fiscal S&T expenditure on regional innovation (Ivus et al., 2021; Tian et al., 2020). However, there are relatively few studies on spatial effects. Third, it did not study the development trends of regional innovation efficiency. This study analyses the relationship between fiscal S&T expenditure and regional innovation efficiency by constructing a spatial convergence model to reveal its specific transmission mechanism.

3. Theoretical mechanism and research hypothesis

The development of regional innovation requires an excellent institutional environment and sufficient innovation elements. As the primary means for the government to support regional innovation, fiscal S&T expenditure not only directly affects the innovation efficiency of various regions, but also guides the spatial flow of innovation elements to affect the dynamic development trend of regional innovation. We explain the internal mechanism of fiscal S&T expenditure affecting the spatial convergence of regional innovation efficiency and propose the research hypothesis of this study.

3.1. The impact of fiscal S&T expenditure on the spatial convergence of regional innovation efficiency

Spatial convergence of regional innovation efficiency is an economic phenomenon based on uneven regional development. With the diminishing marginal efficiency of existing technologies in advanced regions, backward regions have a higher growth rate than developed regions, eventually attaining the convergence of regional innovation efficiency. In the theory of regional development, growth pole and diffusion effects are the key factors that affect this convergence. Market allocation determines the characteristics of the aggregation of innovative elements, which intensifies the imbalance in regional innovation development (Patrick & Hussler, 2005). Fiscal S&T expenditure directly provides innovative elements for the region. Expanding the scale of fiscal S&T expenditure will resolve the problem of the lack of innovative elements in backward areas. This will help make up for market deficiencies, narrow the gap in innovation efficiency between regions, and promote the convergence of regional innovation efficiency. At the same time, fiscal S&T expenditure reflects the government's policy orientation for regional economic planning and development and is an investment signal for investors. Under the guidance of preferential fiscal and taxation policies, the accumulation of capital in the innovation market reduces the risks and costs of enterprise technology investment, improves the level of innovation resource allocation, and promotes the convergence of regional innovation (Montmartin & Massard, 2015). The government also enjoys inherent advantages in leading industrial and regional cooperation. The establishment of fiscal scientific research funds and the establishment of a comprehensive cross-regional industry-university-research cooperation platform is conducive to strengthening the exchange and cooperation of technology research and development and promoting the coordinated development of regional innovation (Liu et al., 2020). It should be noted that excessive government intervention will have a crowding effect on innovation and widen the gap in regional innovation efficiency (Lin & Luan, 2020; Zhou et al., 2020). Therefore, we believe that a simple linear relationship cannot show the relationship between fiscal S&T expenditure and the convergence of regional innovation efficiency well. Therefore, this study proposes the following hypotheses.

Hypothesis 1. *There is an inverted U-shaped nonlinear relationship between fiscal S&T expenditure and the spatial convergence of regional innovation efficiency.*

3.2. Transmission mechanism of fiscal S&T expenditure affecting the spatial convergence of regional innovation efficiency

Technology has a strong externality. The spatial spill-over of technology can help increase the sharing of results and form an excellent collaborative innovation mechanism. The diffusion of technology is mainly affected by the flow of innovative elements. The cross-regional flow of innovation elements breaks the spatial constraints of resources, produces a diffusion effect, and provides opportunities for learning, catching up, and competition for technological progress in backward areas (Li et al., 2020). At the same time, expenditure competition among local governments accelerates the cross-regional flow of R&D elements by affecting the regional innovation environment and the cost of innovation elements. First, the competition for fiscal S&T expenditure can help increase the mobility of R&D personnel (Lenihan et al., 2019). Local governments attract highly educated talents by arranging household registration and housing purchase subsidies, which increases the attractiveness of non-first-tier cities and accelerates the flow of human capital between regions. It also compensates for the disadvantages of backward regional innovation, increases the speed of regional innovation efficiency, and promotes the balanced development of regional innovation efficiency. Additionally, fiscal S&T expenditure has targeted characteristics. Innovative projects supported by the government represent the direction of regional economic development and are a signal to investors in the market. Therefore, market capital will also increase investment in regional innovation fields under the guidance of fiscal S&T expenditure and government credit guarantees (Wu et al., 2020). The innovative competition of fiscal S&T expenditure will provide investors with different fiscal and tax preferential policies, affecting the cross-regional investment in capital. The additional effects of dimension reduction investment under subsidies will help promote the diffusion of the original kinetic energy of technology (Koch & Simmler, 2020) and increase the level of innovation and the speed of development in backward areas. Therefore, we propose the following hypotheses:

Hypothesis 2. *Fiscal S&T expenditure affects the spatial convergence of regional innovation efficiency through the flow of R&D personnel.*

Hypothesis 3. *Fiscal S&T expenditure affects the spatial convergence of regional innovation efficiency through the flow of R&D capital.*

4. Economic models, variables and data

4.1. Economic models

Traditional economic convergence theory was first used to study the differences between the economic growth rates of various countries and then gradually expanded to trade and other fields. In traditional convergence theory, β-convergence means that the economic growth rate of backward areas is faster than that of advanced regions, and the per capita income level of the backward and developed areas converges in the long run. It is an analysis of trends. This study examines the spatial convergence of regional innovation efficiency, which contains spatial correlations and is more in line with social needs. In the design of the spatial convergence model of regional innovation efficiency, we learned from Barro and Sala-I-Martin's (1991) neoclassical growth model using the standard β convergence model as the benchmark model to improve and build a β convergence model of regional innovation efficiency. In this study, β convergence refers to the faster growth rate of innovation production in areas with backward innovation and the convergence of innovation efficiency between regions. Equation (1) is the basic model of β-convergence for regional innovation efficiency.

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta\ln\left(inv_{i,t}\right) + \varepsilon_{i,t} \tag{1}$$

In Equation (1), $inv_{i,t}$ and $inv_{i,t+T}$ are the innovation level of region i from time t to $t+T$, α is a constant term. $\varepsilon_{i,t}$ is the random error term, where β is a convergence coefficient. If $\beta < 0$, it means that regardless of the initial innovation level, all regions will unconditionally reach the same steady state, and there is absolute β convergence in regional innovation efficiency. If $\beta > 0$, it means that there is no absolute β convergence.

Regional innovation activities may have spatial correlation. They may have a mutual influence due to the flow of factors and knowledge spillovers. However, the traditional absolute β-convergence measurement model assumes spatial unrelatedness and homogeneity, which does not conform to the current economic facts of regional innovation. To avoid the distortion of the estimation results caused by the traditional convergence model, we incorporated spatial autocorrelation and spatial error into the traditional convergence model to construct a spatial convergence model to analyse the spatial convergence of regional innovation efficiency. According to the basic theory of the space economy, the central area has the highest level of economic growth and innovation efficiency. Among the neighbouring areas, the closer to the central area, the higher is the level of innovation efficiency. According to the definition of spatial convergence, the development level of the peripheral area is closer to the development level of the central area. As the space approaches the central area, the gap between the regions decreases (Cartone et al., 2021). Therefore, a spatial weight matrix was added to the β-convergence model to construct a spatial convergence economic model. The spatial autoregressive model (SAR) examines the influence of spatial dependence on innovation convergence (Equation (2)). The spatial error model (SEM) examines the effect of regional random errors on innovation convergence (Equation (3)).

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta\ln(inv_{i,t}) + \frac{\rho}{T}w\ln\frac{inv_{i,t+T}}{inv_{i,t}} + \varepsilon_{i,t} \tag{2}$$

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta\ln(inv_{i,t}) + (1-\lambda w)^{-1}\mu_{i,t} \tag{3}$$

In Equations (2) and (3), respectively, ρ is the spatial autoregressive coefficient, which reflects the spatial correlation of the explained variables. It is used to express the influence of the innovation level of adjacent regions on the innovation convergence of the area. λ is the spatial error coefficient, which reflects the spatial correlation between model residuals. w is the $n \times n$-order spatial weight matrix, and we construct a binary space weight matrix based on geographic adjacency (adjacent = 1, non-adjacent = 0). $\varepsilon_{i,t}$ is the random error vector and $\mu_{i,t}$ is the random error vector. Additionally, we considered the control of random errors. This study draws on Islam's (1998) approach, and the explanatory variable adopts the current growth rate, that is, $T = 1$.

If the convergence of regional innovation efficiency is not only related to the initial innovation level but also to other factors, it is necessary to use the conditional β-convergence model for analysis. Conditional β-convergence is based on absolute β-convergence, adding other control variables to study the different steady-state levels caused by differences in economic characteristics (Cartone et al., 2021). The conditional β-convergence model is constructed as shown in Equations (4) and (5).

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta\ln(inv_{i,t}) + \delta_i X_{i,t} + \frac{\rho}{T}w\ln\frac{inv_{i,t+T}}{inv_{i,t}} + \varepsilon_{i,t} \tag{4}$$

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta\ln(inv_{i,t}) + \delta_i X_{i,t} + (1-\lambda w)^{-1}\mu_{i,t} \tag{5}$$

In Equations (4) and (5), respectively, $X_{i,t}$ are other factors that may affect the convergence of regional innovation efficiency, and δ_i is the coefficient of the control

Table 1. Indicators for measuring regional innovation efficiency.

Type	Variable	Description of variables
Input variable	*R & D personnel*	Expressed by the number of R&D practitioners
	R&D capital	Expressed by R&D capital investment
Output variable	*Number of patents granted*	Expressed by the number of patents approved
	Sales revenue of new products	Expressed by product sales revenue obtained from the application of new technologies

Source: Summarized from 4.2.1.

variable. Additionally, the above model can estimate the convergence coefficient β and can also calculate the convergence rate $s = -\ln(1+\beta)/T$ and the convergence period $T = \ln(2)/s$.

4.2. Variables

4.2.1. Regional innovation efficiency (inv)

Presently, the methods for measuring regional innovation efficiency mainly include comprehensive index evaluation, parametric methods (stochastic frontier analysis, SFA) and non-parametric methods (data envelopment analysis, DEA) (Dai et al., 2022; Gerlitz et al., 2020). To avoid the result of the parameter method from being affected by the subjectively set production function, we selected the input-output index and used the DEA-Malmquist index to measure the innovation efficiency (*inv*) of each province (Dobrzanski et al., 2021). Equation (6) is the calculation method for the DEA-Malmquist index.

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \sqrt{\frac{D^t(x^{t+1}, y^{t+1})D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^{t+1})D^{t+1}(x^t, y^{t+1})}} \tag{6}$$

$M(x^{t+1}, y^{t+1}, x^t, y^t)$ represents the Malmquist index, which reflects the change in innovation efficiency from period t to $t+1$. x^t and y^t represent the input and output vectors in period t, respectively, x^{t+1} and y^{t+1} represent the input and output vectors in period $t+1$. D^t and D^{t+1} represent the distance function of the production point between period t and period $t+1$ based on the technology of period t.

According to the stage characteristics of innovation, the indicators of the input variable (x) and output variable (y) were designed. Table 1 presents the variables. Figure 1 shows the measurement results.

4.2.2. Fiscal S&T expenditures (fse)

According to the classification of Chinese government fiscal subjects, we selected technology expenditure in government public expenditure to represent the fiscal S&T expenditure variable (*fse*). To eliminate the influence of the difference in the scale of the regional economy, it was calculated as the proportion of annual fiscal technology expenditure in the total regional fiscal expenditure.

4.2.3. Mediating variables

According to the previous theoretical mechanism analysis, we selected personnel element flow (*pef*) and capital element flow (*cef*) as mediating variables for

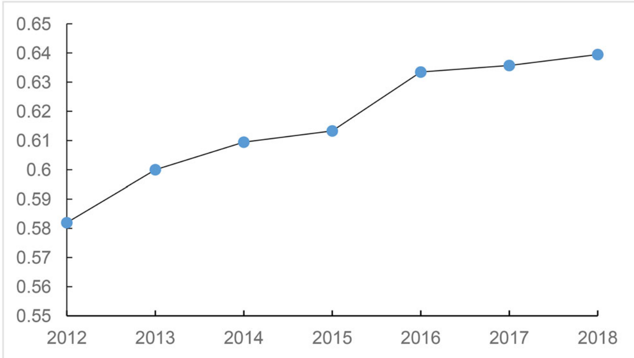

Figure 1. The average innovation efficiency of 30 provinces from 2012 to 2018.
Source: Author's calculation and analysis.

conduction mechanism analysis. The gravity model is widely used to measure international trade, population migration, and cross-regional investment. The flow of personnel elements and the flow of capital elements mainly use the gravity model to measure (Equations (7) and (8)). Wages and housing prices are important factors that affect the flow of labour elements in China. If area i has higher wages or lower housing prices than area j, the R&D personnel in area j will flow to area i under the drive of maximum utility. In practice, local governments in China use higher wages and housing subsidies to attract talent. Therefore, we selected regional average wages (*wage*) and housing prices (*price*) as attractive variables that affect the flow of R&D personnel. At the same time, capital has the characteristics of profit seeking. The difference in profit levels between regions is an important factor affecting capital flows. This study considers profit between regions as an attractive variable that affects the flow of R&D capital elements.

$$pef_i = \sum_{j=1}^{n} pef_{ij} = \ln mp_i * \ln (wage_j - wage_i) * \ln (price_j - price_i) * D_{ij}^{-2} \tag{7}$$

$$cef_i = \sum_{j=1}^{n} cef_{ij} = \ln cp_i * \ln (profit_j - profit_i) * D_{ij}^{-2} \tag{8}$$

Among them, *wage* is the average salary of employees in the region, *price* is the average selling price of residential houses in the region, and *profit* is the average profit rate of enterprises in the region. mp is the number of R&D personnel in the region.cp represents the R&D capital stock in the region.D_{ij} is the distance between regions. pef_{ij} represents the R&D personnel flowing from province i to province j, and cef_{ij} is the amount of R&D capital flowing from province i to province j.

4.2.4. Control variables

To more accurately analyse the impact of fiscal S&T expenditure on the spatial convergence of regional innovation efficiency, we also controlled for the following

Table 2. Descriptive statistics.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
inv	*1*	210	0.616	0.193	0.156	0.959
fse	*1*	210	0.020	0.014	0.007	0.059
pef	*1*	210	0.008	0.006	0.001	0.024
cef	*1*	210	0.167	0.217	0.002	1.143
regdp	*yuan*	210	54636.47	0.410	19710	140211.24
open	*1*	210	0.267	0.297	0.032	1.363
market	*1*	210	6.670	1.916	2.620	9.950
urb	*1*	210	0.566	0.124	0.368	0.893

Source: Authors' processing in Stata15.

variables: ①The level of economic development (*regdp*). The gap in the level of regional economic growth is a critical factor leading to the unbalanced development of regional innovation. We used the logarithm of the regional per capita GDP. ②The level of urbanisation (*urb*). Urbanisation provides an infrastructure for regional innovation. We use the ratio of the regional urban population to the total population to express urbanisation. ③Degree of marketisation (market). The development of regional innovation is inseparable from market support. This is expressed using the marketisation index. ④The level of opening up (open). China's innovation has always benefitted from international capital and technology. This study uses the degree of dependence on regional foreign trade to measure the level of regional openness, which is calculated as the ratio of total imports and exports to GDP.

4.3. Data

This study examines the relationship between fiscal S&T expenditure and the convergence of regional innovation efficiency. Taking into account the impact of changes in data statistics, the completeness of the data, and changes in government innovation policies, we selected 30 provinces in China from 2012 to 2018 (the data of Taiwan, Hong Kong, Macau, and Tibet are seriously missing, so we excluded them) as the research objects. The data in this study were mainly obtained from the WIND financial database, EPS financial database, China National Bureau of Statistics, China Statistical Yearbook, etc. Additionally, we tested the problems of multicollinearity and heteroscedasticity between the variables. The test results showed that these problems do not exist. Table 2 presents the descriptive statistics of the variables. In Table 2, the maximum value of *inv* is 0.959 and the minimum value is 0.193, which indicates that there is a large gap in regional innovation efficiency. It is necessary to study the convergence of regional innovation efficiency. In addition, there is also a large gap in the value of *fse*. The differences of core variables provide realistic evidence for this study.

5. Results and discussion

5.1. Spatial autocorrelation test

We analysed the relationship between fiscal S&T expenditure and the convergence of regional innovation efficiency using a spatial model. Therefore, it was necessary to test spatial autocorrelation between regional innovation efficiency. The spatial neighbourhood matrix can directly express the spatial relationships of the regions. We

Table 3. Moran's I of regional innovation efficiency in 2012-2018.

Year	2012	2013	2014	2015	2016	2017	2018
Moran's I	0.257**	0.261**	0.273***	0.234***	0.245**	0.254***	0.258***
p-value	0.011	0.012	0.006	0.006	0.014	0.009	0.007
Z-statistic	2.449	2.465	2.771	2.766	2.493	2.695	2.728

Note: ***, **represent significance of *p*-values at 1%, 5 %, respectively.
Source: Authors' processing in Stata15.

used the spatial adjacent weight matrix (w) to test the global Moran's I of regional innovation efficiency. Table 3 shows the results. The formula for calculating Moran's I is given by Equation (9).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{9}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2, \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, x represents the regional innovation efficiency, n represents the number of samples, and w is the spatial weight matrix. The value range of *Moran's I* was [-1,1]. When Moran's $\mathrm{I} > 0$, it implies that the innovation efficiency of neighbouring areas is positively correlated. Moran's $\mathrm{I} = 0$ means that the innovation efficiency of neighbouring regions does not correlate. Moran's $\mathrm{I} < 0$ indicates that there are no similar attributes in the innovation efficiency of neighbouring regions.

Table 3 shows that the *Moran's I* of regional innovation efficiency from 2012 to 2018 was greater than 0 and passed the significance test, which indicates that there is a positive correlation between regional innovation efficiency. At the same time, *Moran's I* is between 0.234-0.273, showing a trend of increasing fluctuations. This shows that the spatial dependence of regional innovation efficiency becomes stronger. We used spatial econometrics to be appropriate.

5.2. Spatial econometric model selection

Regional innovation efficiency has a significant spatial correlation, and the next step was to test the rationality of the spatial econometric model. We referred to the method of LeSage and Pace (2009) to carry out the Lagrangian multiplier test (LM), mainly used to identify the rationality of the spatial model. Table 4 shows the test results for the LM and robust LM. As evident, the values of LM (error) 48.24 and robustness LM (error) 184.56 are greater than those of LM (lag) and robustness LM (lag). This indicates that the statistical results of the SEM are better than those of the SAR. We adopted the SEM model. Additionally, to compare the analysis results of different effects, we discussed time-fixed effects (tf), space-fixed effects (sf), and time-space fixed effects (stf).

5.3. Regression analysis

5.3.1. Absolute β convergence of regional innovation efficiency

First, we use Equations (2) and (3) to test whether there is absolute β-convergence in regional innovation efficiency. The results in Table 5 show that the spatial

Table 4. LM test results.

Test	Statistic	*p*-value
Lagrange multiplier(error)	48.24	0.002
Robust Lagrange multiplier(error)	184.56	0.000
Lagrange multiplier(lag)	5.58	0.061
Robust Lagrange multiplier(lag)	174.26	0.000

Source: Authors' processing in Stata15.

autocorrelation values (ρ or λ) of the different models are all greater than 0 and show a certain degree of significance, which indicates that there is a spatial effect on regional innovation efficiency. However, in the absolute β-convergence model, the β value is greater than 0, which indicates that there is no absolute β convergence for regional innovation efficiency. It was necessary to analyse the presence of conditional β-convergence for regional innovation efficiency by controlling fiscal S&T expenditure and other factors.

5.3.2. Conditional β convergence of regional innovation efficiency

There is no absolute β-convergence for regional innovation efficiency. We need to use Equations (4) and (5) to analyse the effect of conditional β-convergence of fiscal S&T expenditure on regional innovation efficiency. Table 6 lists the results.

Table 6 shows that the stf model is significantly better than the sf and tf models. In the regression results of columns (3) and (6), the spatial coefficient (ρ or λ) passed the significance test and was greater than the spatial coefficient of absolute β-convergence. This shows that fiscal S&T expenditure has a significant spatial effect on regional innovation efficiency. At the same time, the β coefficient in the regression result (6) of the SEM model is -0.159, which is significant at the 1% level. The coefficient of fiscal S&T expenditure was 0.128, which also passed the significance test. This shows that there is a condition β convergence for regional innovation efficiency, and the convergence rate (s) is 0.173. Fiscal S&T expenditure has a positive effect on the conditional convergence of regional innovation efficiency. To examine the relationship between fiscal S&T expenditure and the convergence of regional innovation efficiency, we added the square term of fiscal S&T expenditure to the model. In the regression results, the square coefficient of fiscal S&T expenditure is -2.508, which is significant at the 1% level. This confirms our prediction that the relationship between fiscal S&T expenditure and the convergence of regional innovation efficiency follows a quadratic function. They had a significant inverted U-shaped relationship. Thus, hypothesis 1 was confirmed. We also observed the coefficients of the control variables. The variable coefficients of *regdp*, *open*, and *urb* are significantly positive, while the coefficient of *the market* is negative. This shows that economic development, degree of openness, and urbanisation have a positive effect on the convergence of regional innovation efficiency. In contrast, marketisation has an inhibitory effect on the convergence of regional innovation efficiency.

5.3.3. Robustness test

To ensure the reliability of the results, we conducted a robustness test. First, the spatial weight matrix was reset. The spatial adjacent weight matrix assumes that if regions are not adjacent, they are not related. This assumption is not rigorous. The spatial distance matrix avoids this problem. Therefore, we replaced the spatial adjacent weight matrix with the spatial distance weight matrix to redefine the spatial correlation between regions. We re-examined the β-convergence of regional innovation

Table 5. Estimated results of the β absolute convergence of regional innovation effect.

	SAR			SEM		
	(1) tf	(2) sf	(3) stf	(4) tf	(5) sf	(6) stf
B	0.004	0.136***	0.147***	0.004*	0.183***	0.143***
	(1.64)	(5.83)	(4.62)	(1.76)	(6.61)	(4.43)
ρ或λ	0.219**	0.401***	0.221**	0.225**	0.464***	0.179**
	(1.99)	(5.95)	(2.03)	(2.05)	(6.62)	(1.98)
N	210	210	210	210	210	210
R^2	0.301	0.317	0.328	0.402	0.412	0.425
Log-L	613.86	624.33	658.64	614.07	626.82	657.88

Note. ***, **, and * represent significance of *p*-values at 1%, 5% and 10%, respectively.
Source: Authors' processing in Stata15.

Table 6. Estimated results of the β condition convergence of regional innovation.

	SAR			SEM		
	(1) tf	(2) sf	(3) stf	(4) tf	(5) sf	(6) stf
B	0.001	−0.174***	−0.154***	0.001	−0.184***	−0.159***
	(0.21)	(−4.86)	(−4.37)	(0.17)	(−5.36)	(−4.36)
fse	−0.411*	−0.743	0.176**	−0.316**	0.429	0.128**
	(−1.74)	(−0.31)	(2.20)	(−2.16)	(0.36)	(2.23)
fse^2	6.205	−10.057**	−3.208***	4.439	−7.538*	−2.508***
	(1.05)	(−2.18)	(−3.40)	(0.75)	(−1.92)	(−3.31)
regdp	0. 146	0. 197***	0.043**	0.127	0. 297**	0.050**
	(1.41)	(2.93)	(2.20)	(1.28)	(2.35)	(2.23)
open	0.007**	−0.011	0.013**	0.011*	0.003	0.012**
	(2.03)	(−0.57)	(2.49)	(1.76)	(0.17)	(2.44)
market	−0.002***	−0.005	−0.004**	−0.003***	−0.004	−0.005**
	(−2.94)	(−1.56)	(−2.03)	(−3.04)	(−1.00)	(−2.36)
urb	−0.041*	0.081	0.097	−0.044*	−0.013	0.112*
	(−1.73)	(1.13)	(1.61)	(−1.95)	(−0.18)	(1.75)
*ρ*或*λ*	−0.214**	0.402***	0.212**	−0.283**	0.477***	0.221*
	(−1.99)	(5.80)	(2.03)	(−2.46)	(6.47)	(1.87)
s		0.191	0.167		0.203	0.173
t		3.626	4.145		3.409	4.003
N	210	210	210	210	210	210
R^2	0.312	0.363	0.396	0.413	0.427	0.431
Log-L	627.72	627.46	659.78	629.78	628.51	659.71

Note. ***, **, and * represent significance of *p*-values at 1%, 5% and 10%, respectively.
Source: Authors' processing in Stata15.

efficiency. The specific form of the spatial distance weight matrix is: if $i \neq j$, then; $w = 1/D_{ij}$ otherwise, it is 0. D is the spherical geographic distance between regions i and j. We also changed the method of measuring regional innovation efficiency using the stochastic frontier parameter analysis method (SFA) to re-measure regional innovation efficiency and re-analyse the β-spatial convergence of regional innovation efficiency. Table 7 presents the results of the robustness tests.

In Table 7, columns (1) and (2) are the regression results of the spatial distance weight matrix, and columns (3) and (4) show the regression results after changing the regional innovation efficiency measurement method. The results show that the key variables have passed the significance test, the β value is less than 0, the coefficient of fiscal S&T expenditure is greater than 0, and the sign of the coefficient of the square term does not change. The results obtained after replacing the variables are consistent with the previous conclusions, and the conclusions of this study are robust.

Table 7. Robustness test.

	(1) SAR	(2) SEM	(3) SAR	(4) SEM
β	−0.121**	−0.137***	−0.101***	−0.142***
	(−2.11)	(−4.45)	(−3.97)	(−4.36)
fse	0.038**	0.051*	0.024**	0.030***
	(2.34)	(1.73)	(2.08)	(3.28)
fse^2	−2.821*	−2.152**	−3.743**	−2.618**
	(−1.80)	(−2.13)	(−2.31)	(−1.99)
Control variables	YES	YES	YES	YES
*ρ*或*λ*	0.242**	0.259***	0.223**	0.237*
	(2.19)	(4.20)	(2.12)	(1.83)
N	210	210	210	210
R^2	0.237	0.268	0.245	0.279
Log-L	660.05	662.16	660.84	663.03

Note. ***, **, and * represent significance of *p*-values at 1%, 5%and 10%, respectively.
Source: Authors' processing in Stata15.

5.4. Transmission mechanism test

To verify hypotheses 2 and 3, we analysed the mechanism by which fiscal S&T expenditure affects the convergence of regional innovation efficiency. Therefore, this study introduces R&D personnel elements flow (*pef*) and R&D capital elements flow (*cef*) as mediating variables to test the transmission mechanism. The mediation effect test is mainly tested by Equations (10) (11) (12) and (13). Among them, Equations (4), (10), (11) are used to test the mediating effect of the SAR model, and Equations (5), (12), (13) are used to test the mediating effect of the SEM model. When β_1, β_2 and β_3 in Equations (10) and (11) pass the significance test, it indicates the existence of a mediating effect. If they are not significant, there is no mediation effect. When β_4, β_5 and β_6 in Equations (12) and (13) pass the significance test, it indicates the existence of a mediating effect. If they are not significant, there is no mediation effect. *pef* and *cef* are the mediating variables *M*. The mechanism test model includes the control variables. Table 8 lists the results.

$$M_{i,t} = \alpha + \beta_1 \ln(inv_{i,t}) + \delta_i X_{i,t} + \frac{\rho}{T} w \ln\frac{inv_{i,t+T}}{inv_{i,t}} + \varepsilon_{i,t} \tag{10}$$

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta_2 \ln(inv_{i,t}) + \beta_3 M_{i,t} + \delta_i X_{i,t} + \frac{\rho}{T} w \ln\frac{inv_{i,t+T}}{inv_{i,t}} + \varepsilon_{i,t} \tag{11}$$

$$M_{i,t} = \alpha + \beta_4 \ln(inv_{i,t}) + \delta_i X_{i,t} + (1-\lambda w)^{-1}\mu_{i,t} \tag{12}$$

$$\frac{1}{T}\ln\frac{inv_{i,t+T}}{inv_{i,t}} = \alpha + \beta_5 \ln(inv_{i,t}) + \beta_6 M_{i,t} + \delta_i X_{i,t} + (1-\lambda w)^{-1}\mu_{i,t} \tag{13}$$

In Table 8, columns (1) and (4) show the relationship between fiscal S&T expenditure and the flow of innovation elements. Columns (2), (3), (5), and (6) represent the effects of adding the mediating variable. Among them, the coefficient of fiscal S&T expenditure in column (1) is 0.007, which has passed the significance test. In columns (2) and (3), the coefficients of fiscal S&T expenditure and personnel element flow are significantly positive and greater than the β coefficient in Table 6. This shows that fiscal S&T expenditure

Table 8. Test results of transmission mechanism.

	(1) *pef*	(2) SAR	(3) SEM	(4) *cef*	(5) SAR	(6) SEM
B		−0.149***	−0.150***		−0.157	−0.153
		(−4.74)	(−4.66)		(−1.43)	(−1.35)
Pef		8.824**	9.556**			
		(2.24)	(2.13)			
Cef					0.005	0.006
					(0.21)	(0.26)
Fse	0.007***	0.126**	0.133**	0.917	0.139**	0.131**
	(2.65)	(2.11)	(2.14)	(1.35)	(2.17)	(2.13)
Control variables	YES	YES	YES	YES	YES	YES
ρ或λ	0.107**	0.220**	0.220***	0.178*	0.209*	0.194
	(2.13)	(2.01)	(3.84)	(1.93)	(1.90)	(1.63)
S		0.161	0.163		0.171	0.166
T		4.296	4.265		4.059	4.174
N	210	210	210	210	210	210
R^2	0.640	0.245	0.356	0.259	0.244	0.433
Log-L	1587.72	661.20	661.49	431.63	408.91	421.35

Note. ***, **, and * represent significance of *p*-values at 1%, 5% and 10%, respectively.
Source: Authors' processing in Stata15.

promotes the convergence of regional innovation efficiency through the flow of R&D personnel elements. Thus, hypothesis 2 was confirmed. However, column (4) shows that the coefficient of fiscal S&T expenditure is not significant, which indicates that the mediating effect of R&D capital elements flow on the convergence of regional innovation efficiency is not significant. Thus, hypothesis 3 was not effectively confirmed.

5.5. Discussion

The empirical test found that regional innovation efficiency has the characteristics of conditional β-convergence. Fiscal S&T expenditure positively affects the spatial convergence of regional innovation efficiency. This is consistent with the conclusion that fiscal S&T expenditure has compensated for market deficiencies and improved regional innovation efficiency (Montmartin & Massard, 2015). However, the conclusion of the conditional β-convergence that we verified has more practical significance for promoting the balanced development of regional innovation. At the same time, the relationship between fiscal S&T expenditure and the spatial convergence of regional innovation efficiency is inverted U-shaped, which shows that crowding-out effects and government interventions may inhibit regional innovation efficiency (Guo et al., 2016; Li et al., 2017). Additionally, the flow of R&D personnel has a significant mediating effect on the impact of fiscal S&T expenditure on the spatial convergence of regional innovation, and the role of R&D capital flow is not significant. This shows that R&D personnel have a higher knowledge and technology content than R&D capital. R&D personnel are more directly affected by fiscal S&T expenditure, and their effects on regional innovation efficiency may also be more significant (Lenihan et al., 2019).

6. Conclusion and policy implications

This study constructed a spatial β-convergence economic model to study the impact of fiscal S&T expenditure on the spatial convergence of regional innovation efficiency.

The results of this study are as follows. First, the innovation efficiency of different regions in China has a significant spatial correlation and is increasing. Second, China's regional innovation efficiency does not have the characteristic of absolute β-convergence. Fiscal S&T expenditure has a positive effect on the spatial convergence of regional innovation efficiency and has an inverted U-shaped nonlinear relationship as a whole. Third, fiscal S&T expenditure can affect the spatial convergence of regional innovation efficiency by enhancing the flow of R&D elements. Fiscal S&T expenditure can promote the convergence of regional innovation efficiency by improving the flow of personnel elements, but the flow of capital elements has no significant impact.

According to the conclusions of this study, the policy implications have two aspects.

First, it is necessary to establish a scientific fiscal system to improve the efficiency of fiscal S&T expenditure. The development of regional innovation requires fiscal support, but because of the inverted U-shaped relationship between them, it cannot entirely rely on public finances. Therefore, the government must adjust measures to time and local conditions to improve the targeting of fiscal S&T expenditure. For regions with a better foundation for innovation, public finance should play a guiding role in improving the efficiency of fiscal S&T expenditure, providing more space for enterprise innovation, and promoting the transformation of regional innovation structure. For regions with a weak innovation foundation, it is necessary to increase the support of fiscal resources, compensate for the losses caused by the lack of market through fiscal S&T expenditure, and improve the growth rate and quality of regional innovation.

Second, it is necessary to pay attention to the regional relevance in the innovation process. The development of regional innovation efficiency in China has spatial characteristics of relevance and imbalance. Therefore, to realise the coordinated development of regional innovation efficiency, it is important to pay attention to the linkages between regions. On the one hand, the government should build a scientific regional cooperation platform, strengthen the sharing and cooperation of talents and technology between regions, and provide an excellent environmental foundation for the spatial spill-over of technology. On the other hand, while strengthening the market's role in allocating innovation resources, preferential tax policies are given to backward areas to increase the region's attractiveness. It is also possible to help underdeveloped regions achieve innovation catch-up by establishing an innovation support fund. However, it should be noted that the spatial structure of regional innovation must be rationally planned to prevent excessive homogenised competition.

This study has some limitations, which also provide a direction for further research. For example, fiscal S&T expenditure affects the convergence of regional innovation from the level of innovation resources, but the competitive behaviour of local governments may dissimilate the impact of resource allocation. Particularly, under the promotion mechanism of officials, the competition of local governments will have a varied impact on fiscal S&T expenditure and regional innovation efficiency. Additionally, owing to the integrity of the data, the research samples in this study have limitations in terms of the time length and number of regions.

Authors' contribution

Shiying Hou contributed to model analyses, data curation, writing - original draft. Jianjia He contributed to writing - review & editing, framework. Liangrong Song contributed to writing - review & editing, supervision, framework.

Declaration of competing interest

No potential conflicts of interest are related to this article.

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