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Science and Technology Resource Allocation, Spatial Association, and Regional Innovation

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Abstract: Considering the impact of science and technology resource allocation on regional innovation output, based on the inter-provincial panel data of 30 provinces in China from 1998 to 2017, this paper establishes a regional innovation output growth model, including science and technology resource input and science and technology resource allocation, and investigates the spatial relationship between regional innovation output and the allocation of science and technology resources, the effect of the inter-subjective configuration structure and inter-regional space re-allocation on regional innovation output. The research results show that there are obvious spatial autocorrelation agglomeration characteristics of China's regional innovation output and science and technology resource input. The efficiency of the allocation of science and technology resources in the region is relatively low. The application-oriented research subjects with enterprise-oriented research are more efficient in investing in science and technology resources, and the promotion of regional innovation output is more significant. The investment in science and technology resources in neighboring provinces will have a significant inhibitory effect on the province's innovation output. The regional mobility of science and technology resources has a significant role in promoting regional innovation output growth. The effect of science and technology personnel mobility on regional innovation output is better than that of technology capital flows.

Keywords: science and technology resource allocation; spatial association; regional innovation; spatial econometrics

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1. Introduction

Long-term sustained economic growth is the result of technological advancement. In the past 40 years, China's economy has achieved unprecedented development results, but there are still deficiencies such as low quality, low efficiency, low innovation, and inefficient development of the real economy. This urgently requires China to change its traditional economic growth model, change the structure of economic growth, and improve the quality of economic development. In 2019, Premier Li Keqiang emphasized in the Government Work Report, that the government would "increase support for basic research and applied basic research, strengthen original innovation, and strengthen key core technology research." Economic growth in the new period requires the Chinese economy to change from past factors and being investment-driven to an innovation-driven growth model, relying on innovation as an engine of economic growth and improving production efficiency. Scientific and technological innovation has gradually become the new normal for China's ongoing economic growth.

In recent years, the intensity and scale of investment in science and technology resources in various places have continued to expand. The national research and experimental development funding input intensity increased from 1.66% in 2009 to 2.13% in 2017, and the proportion of research and experimental development funding to Gross Domestic Product (GDP) continued to increase from 1995 to 2017, from 0.57% to 2.13%. The investment in science and technology resources is increasing, but China's technological level has not increased significantly. Zhang et al. held that the overall level of innovation in China's industry is low, indicating that the potential of scientific and technological resources has not been fully explored [1].

China's early innovation subjects formed a path dependence on technology introduction and imitation, but the proportion of scientific and technological resources in basic research was very low. In 2017, the proportion of Research and Development (R&D) basic research expenditure was only 5.5%, which greatly hindered innovation development. The China Regional Innovation Capability Evaluation Report 2018 shows that with the regional agglomeration of China's scientific and technological resources, the distribution of scientific and technological resources has shown significant regional differences, but the innovation capabilities and efficiency differences between regions also continue to expand. Zhao [2] believes that administrative division and geographical distance are the main constraints on the flow of production factors in China, and it is easy to waste innovation resources. China's R&D resources show a "Matthew effect" allocation pattern, leading to an imbalance in the distribution of regional innovation capabilities in China, which basically forms a pattern that the eastern region ranks ahead and the central and western regions lag behind, and the gap between the eastern and central and western regions gradually widens. At present, it is unreasonable to study the allocation of science and technology resources from the static level. Additionally, the biggest contribution of this research is to study the flow of the resources of science and technology in space, thus for the regional innovation spillover effect, rather than discussing the validity of resources configuration of input and output efficiency of science and technology, and explore how to make science and technology resources of enterprises, universities, research institutions achieve in the space between optimization, promote the improvement of innovation, and reduce regional differences between innovation level.

The rest of this paper is arranged as follows: Section 2 reviews relevant studies on science and technology resources, including studies on allocation efficiency of science and technology resources and the spatial agglomeration degree of science and technology resources of different regional subjects. Section 3 is about setting models, variable selection, and data sources. Section 4 includes a spatial correlation test of scientific and technological resources. Section 5 is about the empirical test and result analysis, including spatial measurement results within and between regions.

2. Literature Review

In recent years, as a national strategic resource, scientific and technological resources have attracted the attention of academic circles. Some scholars have constructed index systems from different angles and used different function models to measure the efficiency of scientific and technological resource allocation. Feng et al. used the number of new product development as the output index of R&D activities, the total amount of R&D funding and the number of technical personnel as input indicators, and found that the efficiency of China's industrial research and development is relatively low [3]. Zhu and Xu used the stochastic frontier production function to take the sales revenue of new products as the output indicator of R&D activities, R&D capital investment and R&D personnel as input indicators, and calculated the innovation efficiency of China's high-tech industry [4]. Zhang and Shi measured the technical efficiency of new products through the directional distance function and analyzed that China's industrial R&D investment is inefficient [5]. Zhou [6] used the generalized Cobb–Douglas production function and measured the accumulated capital of R&D as a variable to measure the company's knowledge capital. It was found that the accumulation of R&D activities such as product and technological innovation has increased the productivity of enterprises. Fan used the exploratory spatial data analysis (ESDA) analysis method to find that there is spatial autocorrelation in the allocation efficiency of science and technology resources between cities and a phenomenon of spatial agglomeration between similar values [7]. Li et al. [8] constructed an evaluation index system for the allocation of regional scientific and technological resources and used the Gini coefficient and Theil index to study the differences in the allocation of scientific and technological resources in various regions. Finally, using ESDA to study the spatial agglomeration characteristics of science and technology resource allocation capabilities in various provinces, Shi et al. used the technology input–output index system to use Data Envelopment Analysis's (DEA's) super-efficiency CCR model and Malmquist index model to evaluate the efficiency of science and technology resource allocation in 30 provinces in China [9]. Li and Wen [10] used the data of "financial resources" and "innovative achievements" from 2009 to 2016 to construct a relevant evaluation index system. They all found that China's science and technology resource allocation capacity has improved, but the efficiency of science and technology resource allocation across regions still has regional differences and continues to expand.

Different innovation entities in the region have brought together the state of scientific and technological resources, established a "government–market" joint allocation model, and developed cooperatively through sharing to realize redistribution, promote regional innovation, promote scientific and technological progress, and improve the operational efficiency of scientific and technological activities [11,12]. Under the mechanism of open sharing of scientific and technological resources, Dahlander [13] believes that scientific and technological innovation resources will not automatically flow into enterprises, and enterprises need to establish a supporting culture, structure, and path to encourage the sharing of scientific and technological innovation resources. Starting from the thinking logic of collaborative innovation, Yue and Zhu established a rational cooperative innovation benefit distribution mechanism to ensure resource sharing based on the basic principles of game theory [14]. Huang and Xie [15] carried out a quantitative measurement of the scientific and technological resource agglomeration and collaborative innovation effects in the Yangtze River Economic Belt and found that the agglomeration degree in Jiangsu, Zhejiang, and Shanghai is much higher than in other regions. Regional differences are obvious, showing a gradient pattern of eastern, central, and western regions. Although the Yangtze River Economic Belt as a whole has a certain degree of synergistic innovation effects, the synergetic innovation effects within the central region and between the central and western regions are low. Ye and Liu [16] believe that government support should be targeted, and scientific research should be vigorously supported, and companies and markets should be allowed to develop technology. This can not only avoid the inefficiency generated by heterogeneous research and development but also help to solve the dilemma of China's technological innovation.

The above literature expounds the allocation efficiency of science and technology resources from different perspectives of establishing an index system, using a function model, and realizing the collaborative sharing of science and technology resources. It can be found that most of the research are based on the perspectives of various innovation subjects and spatial distribution patterns in the region. Few scholars have studied the specific impact on regional innovation output from the aspect of the spatial allocation of regional scientific and technological resources. With the rise of regional innovation research, scholars' research has gradually turned to the spatial correlation direction of regional innovation, and this article integrates the resource allocation between different technological innovation subjects in the region and the spatial correlation generated by the dynamic flow of scientific and technological resources within the region. The analysis reveals the efficiency of scientific and technological resource allocation in the regional innovation system and its impact on regional innovation output. Specifically, using data from 1998 to 2017, based on global spatial autocorrelation and local spatial autocorrelation, it analyzes the spatial correlation between innovation output and scientific and technological resource input in 30 provinces in China, explores the spatial correlation between the allocation of scientific and technological resources and regional innovation output in each province, and focuses on the specific impact of the allocation of science and technology resources on regional innovation output by the three major research and development areas of enterprises, universities, and research institutions.

3. Methodology

3.1. Model

Research on scientific and technological resources and regional innovation growth is generally based on the knowledge production function, and key points are adjusted accordingly during the research [17]. The most important feature of the knowledge production function is that the input scale of R&D resources is the determinant of knowledge production. The more R&D investment, the faster the knowledge stock increases, thereby promoting technological progress and productivity improvement [18]. Not only the scale of investment in scientific and technological resources but also the efficiency of scientific and technological resource allocation are important factors affecting regional innovation and growth. Under the condition that the scale of investment in scientific and technological resources remains the same, if there is a mechanism that enables science and technology resources to flow back from lower productivity companies to higher productivity companies, and then from the slower areas of innovation to the leading areas of innovation and development, the level of innovation development of the entire country will also show an upward trend.

Therefore, referring to the existing research, this paper chooses the knowledge production function of Griliches [19] and Jaffe [20] as the basic measurement model. Regional innovation is mainly affected by the scale of science and technology resource input and the efficiency of science and technology resource allocation. The input factors mainly include R&D capital investment and R&D personnel, and an innovative production function (Equation (1)) is obtained.

$$Y_{it} = A_{it} \times K_{it}^{\alpha} \times L_{it}^{\beta} \times {D_{it}}^{\gamma} \tag{1}$$

where Y is the innovation output, A is the efficiency of the allocation of scientific and technological resources, K is the investment in research and development capital, L is the investment in research and development personnel, and D is the environmental factor affecting regional innovation, mainly considering foreign direct investment [16].

Take the natural logarithms on both sides of Equation (1) and replace the corresponding variable symbols to obtain the following regional innovation growth regression model (Equation (2)).

$$\ln INNO_{it} = c + \beta_0 \times \ln RDE_{i,t-1} + \beta_1 \times \ln RDP_{i,t-1} + \beta_2 \times \ln FDI_{it} + \mu_{it} \tag{2}$$

Among them, $INNO_{it}$ is the innovation output in province i and year t; RDE_{it} is the investment of science and technology capital in province i and year t; RDP_{it} is the input of science and technology personnel in province i and year t; and FDI_{it} is the level of foreign direct investment in province i and year t; β_0, β_1 and β_2 respectively represent the output elasticity of science and technology capital, science and technology personnel, and foreign direct investment.

First, considering the role of the allocation of scientific and technological resources within the province to the growth of regional innovation, different R&D subjects focus on different research objects in scientific and technological activities. The scientific and technological innovation activities of universities and research institutions can provide a theoretical basis for corporate innovation, and there are significant internal links between the three types of innovation subjects [17]. The coordination and allocation of scientific and technological resources among different subjects is very important to improve the level of regional innovation output. Therefore, we establish the following measurement model (Equation (3)).

$$\begin{aligned}\ln INNO_{it} = c + \beta_0 \times \ln RDE_{i,t-1} + \beta_1 \times \ln RDP_{i,t-1} + \beta_{2\theta} \times \ln SRDE_{\theta,i,t-1} + \beta_{3\theta} \times \ln SRDP_{\theta,i,t-1} + \\ \beta_4 \times \ln FDI_{it} + \mu_{it}, \theta = C, X, Y\end{aligned} \tag{3}$$

where C, X and Y represent the enterprise, university, and research institution; $SRDE_{\theta it}$ and $SRDP_{\theta it}$ respectively represent the technological capital and personnel share occupied by θ innovation subject; $\beta_{2\theta}$ and $\beta_{3\theta}$ are the allocation efficiency of science and technology resources of different research subjects.

Further, in examining the impact of the cross-regional allocation of scientific and technological resources on regional innovation output, we introduced the flow of technology capital and the flow of technology personnel. The regional flow of science and technology resources connects decentralized economies into a whole, making some resources with low innovation output into a production process with high innovation output, realizing the reconfiguration of science and technology resources. At the same time, the free flow of scientific and technological resources will lead to competition among regional innovation activities. In order to attract more high-quality scientific and technological resources and enable scientific and technological resources to be used more effectively, regions must continue to improve the innovation environment [21]. Thus they have an impact on regional innovation activities and innovative changes in output. Therefore, the measurement model is extended to the following model (Equation (4)).

$$\begin{aligned} \ln INNO_{it} &= c + \beta_0 \times \ln RDE_{i,t-1} + \beta_1 \times \ln RDP_{i,t-1} + \beta_{2\theta} \times \ln SRDE_{\theta,i,t-1} \beta_{3\theta} \times \ln SRDP_{\theta,i,t-1} \\ &\quad + \beta_4 \times \ln FRDE_{i,t-1} + \beta_5 \times \ln FRDP_{i,t-1} + \beta_6 \times \ln FDI_{it} + \mu_{it}, \theta = C, X, Y \end{aligned} \tag{4}$$

where $FRDE_{it}$ and $FRDP_{it}$ are the scientific and technological capital and personnel input flowing into the province each year, β_4 and β_5 are the effects of regional flow of scientific and technological resources on regional innovation output, and the plus and minus signs indicate the efficiency of the allocation of technological resources across regions.

Regional innovation growth in a region is not only affected by the scale and allocation efficiency of science and technology resources in the region. Due to the spillover effects of science and technology resource activities, the mobility of science and technology resources, and the effects of policy demonstration [22], there is a spatial correlation of innovation output in various regions. Additionally, similar to public goods, innovation output also has positive externalities. Innovation output in other provinces can be used by the province through diffusion effects or spillover effects. Compared with traditional economic resources, scientific and technological resources usually carry more technical knowledge during the flow process, promote the flow and application of new technologies between regions, and strengthen the linkage of innovation output between regions. With the implementation of the innovation-driven strategy, the proportion of science and technology investment in GDP has been included in the scope of provincial government performance evaluation. The science and technology investment policy of one province will be affected by the scale of science and technology investment of other provinces, which will, in fact, increase the connection between different provinces and strengthen the space dependence of different provinces. When there is spatial dependence, spatial measurement is needed to explain the relationship between variables to avoid over-interpretation or neglect [23]. Spatial econometric models mainly include the spatial lag model (SLM) and the spatial error model (SEM). When the spatial effect between variables appears to be critical to the model and results in spatial autocorrelation, SLM is used; when there is autocorrelation in the error terms of the model, SEM is used [24]. In order to analyze the impact of the spatial spillover effect of the investment in scientific and technological resources on the level of regional innovation, the variable of the technological resource spillover level is introduced in Equation (4), and the SLM model is set as Equation (5).

$$\begin{aligned} &\ln INNO_{it} = c + \rho \sum_{j=1}^{30} \omega_{ij} \ln INNO_{jt} + \beta_0 \times \ln RDE_{i,t-1} + \beta_1 \times \ln RDP_{i,t-1} + \beta_{2\theta} \times \ln SRDE_{\theta,i,t-1} + \beta_{3\theta} \times \ln SRDP_{\theta,i,t-1} \\ &+ \beta_4 \times \ln FRDE_{i,t-1} + \beta_5 \times \ln FRDP_{i,t-1} + \beta_6 \times \ln WRDE_{i,t-1} + \beta_7 \times \ln WRDP_{i,t-1} + \beta_8 \times \ln FDI_{it} + \mu_{it},\ \theta = C, X, Y \end{aligned} \tag{5}$$

The SEM model is set as Equation (6).

$$\begin{aligned} &\ln INNO_{it} = c + \beta_0 \times \ln RDE_{i,t-1} + \beta_1 \times \ln RDP_{i,t-1} + \beta_{2\theta} \times \ln SRDE_{\theta,i,t-1} + \beta_{3\theta} \times \ln SRDP_{\theta,i,t-1} + \beta_4 \times \ln FRDE_{i,t-1} \\ &+ \beta_5 \times \ln FRDP_{i,t-1} + \beta_6 \times \ln WRDE_{i,t-1} + \beta_7 \times \ln WRDP_{i,t-1} + \beta_8 \times \ln FDI_{it} + \mu_{it}, \theta = C, X, Y, \mu_{it} = \lambda \sum_{j=1}^{30} \omega_{ij} \mu_{it} + \varepsilon_{ij} \end{aligned} \tag{6}$$

where $\ln WRDE_{it} = \sum_{j=1}^{30} \omega_{ij} \ln RDE_{jt}$, $\ln WRDP_{it} = \sum_{j=1}^{30} \omega_{ij} \ln RDP_{jt}$, $i \neq j$; $i = j, \omega_{ij} = 0$. $\ln WRDE_{it}$ and $\ln WRDP_{it}$ indicate that the i provinces are affected by the technological capital and personnel input of other provinces, and measure the impact of spatial spillover effects of investment in science and technology resources on regional innovation output. Notably, ω_{ij} is an element of the $n \times n$ weight matrix used to reveal the spatial linkages among all geographic units and is the key set distinguishing the spatial econometric model from the conventional models. n is the number of regions.

The spatial weight matrix can represent the interdependence and correlation between regions. Selecting a reasonable spatial weight matrix is very important for analyzing the spatial spillover effect of regional innovation output. For research needs, this paper establishes spatial weight matrices from three perspectives of geographic proximity in order to better analyze the spatial spillover effect of regional innovation output.

3.1.1. Adjacency Matrix

Economic and innovative development is closely related to its spatial location. In geographically adjacent areas, there is a clear correlation between innovation activities. The geographical proximity spatial weight matrix is mainly divided into two types: one is the "adjacent matrix" which is a spatial weight matrix constructed according to the adjacent relationship between regions. The specific definition method is as follows, assuming that ω_{ij} is an element in the space weight matrix ω whose coordinates are (i, j). If there is a common boundary or node between i and j, the corresponding element ω_{ij} in the spatial weight matrix is assigned a value of 1; otherwise, the assignment value is 0 [25]. So the adjacent matrix is set as Equation (7).

$$\omega_{ij} = \begin{cases} 1, & \textit{there is a common boundary or node between } i \textit{ and } j \\ 0, & \textit{there is no common boundary or node between } i \textit{ and } j \end{cases} \quad (i \neq j) \tag{7}$$

3.1.2. Distance Matrix

The spatial effect of regional innovation activities is not limited to the neighboring regions. The innovation strategy of a province can be observed by all provinces, and the magnitude of its impact is inversely proportional to the distance between the two provinces [25]. "Distance matrix" is a distance weight matrix according to a distance function between regions. This paper chooses the inverse square space matrix of distance proposed by Anselin (1995) [26] to illustrate the effect of the innovative interaction relationship between regions that decays with increasing distance. Specifically, we measure geographic proximity as the reciprocal of the distance between areas i and j. So the distance matrix is set as Equation (8).

$$\omega_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \tag{8}$$

where d_{ij} represents the Euclidean distance of provinces i and j, measured by ArcGIS ver. 10.6 (American ESRI Corporation, Redlands, CA, USA).

In terms of geographic distance, this article also refers to the method of Jiao et al. [17] and adjusts based on Equation (8) to establish a new spatial weight matrix (Equation (9)).

$$\omega_{ij} = \begin{cases} \frac{W_{ij}(d)}{\sum_{j=1}^{30} W_{ij}(d)}, i \neq j \\ 0, \quad i = j \end{cases} \tag{9}$$

where $W_{ij}(d) = \frac{1}{d_{ij}^2}$, and d_{ij} represent the Euclidean distance of provinces i and j, measured by ArcGIS ver. 10.6.

Of course, some scholars have also established a technical distance spatial weight matrix [27], but Qu and Lee [28] believe that this type of spatial weight matrix is seriously endogenous, so this paper does not adopt such a spatial weight matrix.

3.2. Data Source

In this paper, panel data from 30 provinces in China from 1998 to 2017 were used as samples. Because Tibet has a lot of missing data, it was deleted. A very small number of annual data in other provinces were all assigned a value of 0.10 [29]. The original data comes from the China Statistical Yearbook, the China Statistical Yearbook of Science and Technology, provincial statistical yearbooks, and relevant databases of the State Intellectual Property Office. The data of each variable is processed as follows:

(1) Explained variable: Regional Innovation Output (INNO). Expressed by the number of invention patent applications [30]. In developing countries, innovation capabilities are at the stage of imitation and learning, and patents can better reflect the value of innovation activities [31]. The number of invention patent applications rather than grants is used to reflect the degree of innovation output in China's provinces because the patent application itself reflects the process of R&D activities and the cost of holding it regardless of whether the patent is authorized or not [32]. Moreover, in the Chinese context, the amount of invention patents granted is greatly affected by human factors such as government patent agencies.

(2) Core explanatory variables: (i) Input of scientific and technological resources, including technology capital investment (RDE) and technology personnel investment (RDP). There are two main methods for measuring technology capital investment: one is the internal expenditure of R&D funds, and the other is the R&D capital stock. To accurately measure the impact of technological capital investment on regional innovation output, a calculation of R&D capital stock is needed. This paper draws on Yu [31] estimation method of R&D capital stock to obtain the R&D capital stock of 30 provinces in China from 1998 to 2017 (Equation (10)).

$$RDE_{it} = (1 - \delta)RDE_{i,t-1} + (1 - 0.5\delta)KR_{it} \quad (10)$$

Among them, KR_{it} is the internal expenditure of R&D expenditures in province i and year t, and δ is the depreciation rate (10%).

(ii) Allocation of scientific and technological resources among R&D subjects. It is expressed as the ratio of the investment in scientific and technological capital and the input of scientific and technological personnel in enterprises, universities, and research institutions to the total investment in regional scientific and technological personnel [17]. There are many indicators for measuring the input of scientific and technological personnel in a region, such as the number of scientific and technological activities, the number of scientists and engineers, and the full-time equivalent of R&D personnel. Among them, the full-time equivalent of R&D personnel can most accurately describe the human input of scientific and technological activities [33]. (iii) The flow of scientific and technological resources between regions, including technology capital flow (FRDE) and technology personnel flow (FRDP), measured by the gravity model. The gravity model is the development and application of the law of universal gravitation in the field of economics in physics. It is mainly used to analyze the problem of space interaction in an economic society [17]. This paper borrows from Bai and Jiang [33] to use the gravity model to measure the degree of spatial correlation between regional scientific and technological capital and personnel flows and selects a double logarithmic gravity model to measure the flow of scientific and technological resources between two regions in year t (Equations (11) and (12)).

$$FRDE_{ijt} = \frac{RDE_{it} \times RDE_{jt}}{d_{ij}}, i \neq j \quad (11)$$

$$FRDP_{ijt} = \frac{RDP_{it} \times RDP_{jt}}{d_{ij}}, i \neq j \quad (12)$$

where $FRDE_{ijt}$ and $FRDP_{ijt}$ are the flow of science and technology capital and science and technology personnel between provinces i and j. Therefore, the total flow of scientific and technological capital and scientific and technological personnel in the province i are as Equations (13) and (14).

$$FRDE_{it} = \sum_{j=1}^{30} FRDE_{ijt}, i \neq j \quad (13)$$

$$FRDP_{it} = \sum_{j=1}^{30} FRDP_{ijt}, i \neq j \quad (14)$$

(3) Controlling variables: The level of regional openness (FDI) can reflect the level of regional technology introduction, expressed as the proportion of total foreign direct investment in GDP. In the process of innovation, the communication and learning between the innovation subject and the outside world can have an important impact on the innovation output of the region. Generally, the higher the degree of openness, the easier it is for external advanced technology to spill over into the region, and the easier it is to attract more external technology investment. In addition, the entry of foreign investment will also form a competitive incentive for enterprises in the region, thereby promoting the development of innovation in the region [34] (Table 1).

Table 1. Variables, measurements, and data sources (N = 600).

Variables	Abbreviations	Data Source
The number of invention patent applications	INNO	China Statistical Yearbook (1998–2017) [35]
Intramural expenditure on R&D	RDE	China Statistical Yearbook on Science and Technology (1997–2016) [36]
R&D capital stock	RDP	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDE share occupied by the enterprise	CRDE	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDE share occupied by the university	XRDE	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDE share occupied by the research institution	YRDE	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDP share occupied by the enterprise	CRDP	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDP share occupied by the university	XRDP	China Statistical Yearbook on Science and Technology (1997–2016) [36]
RDP share occupied by the research institution	YRDP	China Statistical Yearbook on Science and Technology (1997–2016) [36]
The flow of RDE	FRDE	China Statistical Yearbook on Science and Technology (1997–2016) [36]
The flow of RDP	FRDP	China Statistical Yearbook on Science and Technology (1997–2016) [36]
Foreign direct investment	FDI	China Statistical Yearbook (1998–2017) [35]

4. Spatial Correlation Test

4.1. Global Moran's I Statistics

Moran's I index can reflect the average correlation degree between spatially adjacent or spatially adjacent regional units and the aggregation of spatial distribution [37,38]. The calculation formula is as Equation (15).

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\overline{x})\left(x_j-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\overline{x})\left(x_j-\overline{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{15}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2, \overline{x} = \frac{1}{n}\sum_{i=1}^{n}x_i$, x_i is the observation value of the i space unit, n is the number of space units, ω_{ij} is the spatial weight matrix. The Moran's I index takes a value between [−1,1]. A positive index indicates that there is a spatial positive correlation. The observed attributes show a clustering spatial pattern. The closer to 1, the stronger the positive correlation. A negative index indicates that there is a negative spatial correlation, and the observed attributes are in a discrete spatial pattern. The closer to −1, the stronger the negative correlation. An index of 0 indicates that there is no spatial correlation and it is randomly distributed in space [34,39].

Table 2 shows the Moran's I values of innovation output, scientific and technological capital investment, and scientific and technological personnel input in 30 provinces in China from 1998 to 2017.

Table 2. Moran 's I value of INNO, RDE, and RDP from 1998 to 2017.

Year	INNO		RDE		RDP	
	Moran's I	Z	Moran's I	Z	Moran's I	Z
1998	0.0369 *	1.3008	0.0327 *	1.1837	0.0706 *	1.6121
1999	0.0559 *	1.5081	0.0192	0.901	0.0733 **	1.6238
2000	0.0499 *	1.4589	0.0481 *	1.4270	0.0785 **	1.7273
2001	0.0454 *	1.4530	0.0420 *	1.1917	0.1011 **	2.0859
2002	0.0504 *	1.5702	0.0615 *	1.5097	0.0892 **	1.8843
2003	0.0837 **	2.0125	0.0687 *	1.5935	0.0997 **	2.0209
2004	0.0592 **	1.6961	0.0984 **	2.0470	0.1025 **	2.2711
2005	0.0663 **	1.7973	0.1122 **	2.2368	0.1098 **	2.3538
2006	0.0818 **	1.9118	0.1290 **	2.4597	0.1243 **	2.4685
2007	0.0916 **	2.0303	0.1267 **	2.3897	0.1060 **	2.2267
2008	0.0925 **	2.0049	0.1324 **	2.4636	0.1074 **	2.2728
2009	0.0969 **	2.0677	0.1290 **	2.4189	0.1324 ***	2.7192
2010	0.0966 **	2.0795	0.1210 **	2.2995	0.1261 **	2.6741
2011	0.0979 **	2.2126	0.1262 **	2.3928	0.1291 **	2.7319
2012	0.0915 **	2.1267	0.1286 **	2.4194	0.1181 **	2.5794
2013	0.1033 **	2.2170	0.1295 **	2.4439	0.1304 ***	2.7595
2014	0.1127 **	2.3055	0.1299 **	2.4610	0.1375 ***	2.8740
2015	0.1144 **	2.3227	0.1271 **	2.4078	0.1425 ***	2.9572
2016	0.1185 **	2.3978	0.1266 **	2.3982	0.1437 ***	2.9818
2017	0.1006 **	2.2067	0.1287 **	2.4590	0.1349 ***	2.8433

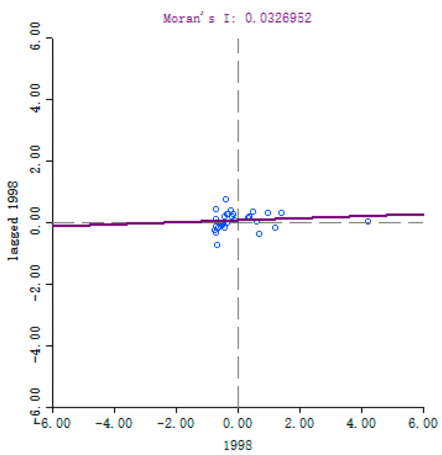
Note: *, **, *** indicate that they passed the significance test at the levels of 10%, 5%, and 1%.

As can be seen from the table, the Moran's I values of regional innovation output from 1998 to 2017 were all greater than 0, and all passed the test at a significance level of 10%, even most of them passed the test at a significance level of 5%. This shows that the spatial distribution of regional innovation output in China is not random. There is a spatial positive correlation between regional innovation output and spatial clustering characteristics. That is, provinces with higher innovation intensity tend to be closer to other provinces with higher innovation intensity. Provinces with low innovation intensity are close to other provinces with low innovation intensity [40]. On the whole, the overall Moran 's I value of China's regional innovation output generally shows a process of rising, then falling, and then rising, but this does not affect the study of its correlation characteristics. Technological capital and personnel input have similar characteristics of spatiotemporal changes, and both Moran 's I values are significantly positive. This shows that there is a significant spatial correlation between China 's investment in science and technology resources; that is, there is a significant spatial agglomeration effect between provinces with similar investment in science and technology resources. In addition, from 1998 to 2017, the Moran's I value of science and technology capital investment increased from 0.0327 to 0.1287, and the Moran's I value of science and technology personnel investment increased from 0.0706 to 0.1349. With the development, the overall investment in science and technology resources has shown an upward trend. The increase in Moran's I value is mainly due to the rapid acceleration of the flow of science and technology resources between provinces, the increasing interaction between provinces. Provinces with high levels of innovation resources investment and low-intensity provinces are more closely linked with each other in terms of innovation activities, thereby strengthening the spatial dependence of science and technology resources.

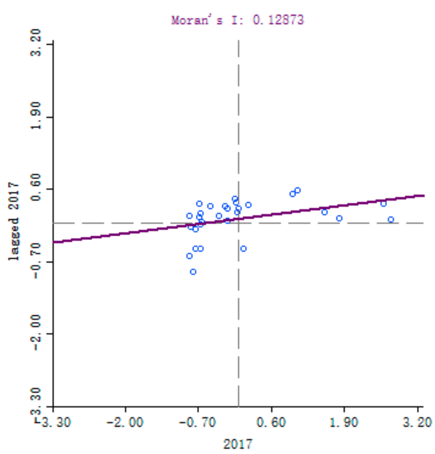
4.2. Local Moran's I Statistics

In order to deeply study the specific form of spatial agglomeration of scientific and technological resources, local spatial correlation analysis methods were used to analyze local Moran results with GeoDa ver. 1.14 (University of Chicago Spatial Data Science Center, Chicago, IL, USA), as shown in Figure 1.

Figure 1 shows the scatter plot of Moran 's I invested in science and technology resources in 30 provinces of China in 1998 and 2017. The first quadrant of the Moran 's I scatter plot belongs to the high investment in scientific and technological resources–high spatial lag (H–H) agglomeration form [41]. The second quadrant belongs to the low investment in scientific and technological resources–high spatial lag (L–H) agglomeration form. The third quadrant belongs to the low investment in scientific and technological resources–low spatial lag (L–L) agglomeration form,. The fourth quadrant belongs to the high investment in scientific and technological resources–low spatial lag (H–L) agglomeration form,. Among them, the clustering features in the first and third quadrants indicate positive spatial correlation, and the clustering features in the second and fourth quadrants indicate negative spatial correlation. In 1998, the scientific and technological personnel investment in 19 provinces showed a positive spatial correlation, of which 9 provinces were located in the first quadrant, showing the H–H agglomeration form. In 2017, 63.3% of the province's scientific and technological personnel investment showed a positive spatial correlation, and the remaining regions showed a negative correlation. Science and technology capital investment have similar characteristics. This shows that the scientific and technological resource inputs of most provinces show a positive spatial correlation in geographic space, and the slope of the regression fitting line has increased, indicating that this positive spatial correlation is constantly strengthening.

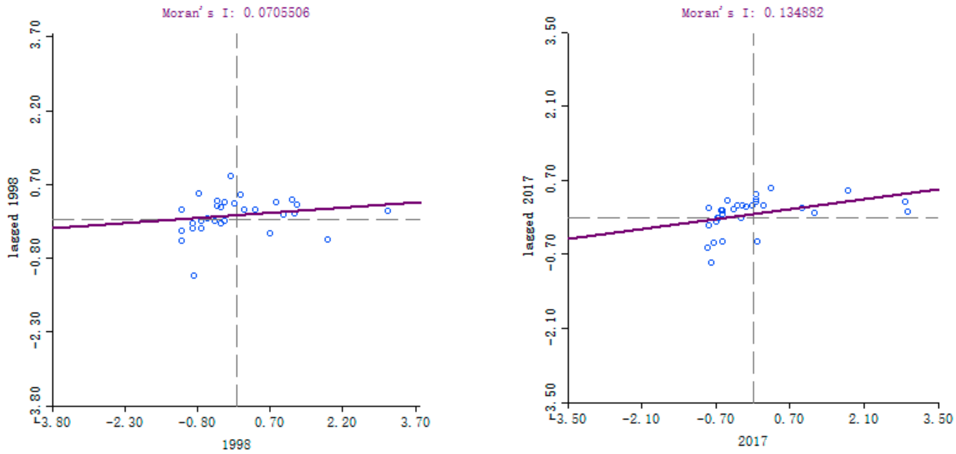


(**a**)



(**b**)

Figure 1. *Cont.*



(**c**) (**d**)

Figure 1. Scatter diagram of Moran 's I invested in scientific and technological resources; (**a**) RDE in 1998, (**b**) RDE in 2017, (**c**) RDP in 1998, (**d**) RDP in 2017.

5. Empirical Test and Result Analysis

5.1. Analysis of Spatial Metrology Results in the Region

In order to examine the resource allocation efficiency of different innovation subjects in the region, the least squares method (OLS) was used to analyze the impact of the share of science and technology resources input of different innovation subjects on regional innovation output, as shown in Table 3.

Table 3. Least squares method (OLS) results of the regional allocation of technological resources on innovation impact.

Variables	CRDE	XRDE	YRDE	Variables	CRDP	XRDP	YRDP
CRDE	0.1859 *** (3.5)			CRDP	0.3741 *** (3.87)		
XRDE		0.0487 (1.26)		XRDP		−0.3995 *** (−5.11)	
YRDE			−0.0277 (−1.00)	YRDP			−0.2119 *** (−3.7)
RDE	1.0316 *** (63.51)	1.0438 *** (63.77)	1.0393 *** (62.17)	RDP	1.2352 *** (35.05)	1.2058 *** (31.89)	1.2400 *** (33.10)
WRDE	−0.5966 *** (−3.62)	−0.6155 *** (−3.73)	−0.6349 *** (−3.90)	WRDP	−0.7618 ** (−2.04)	−0.9402 ** (−2.56)	−0.7036 * (−1.88)
FDI	0.0872 *** (2.93)	0.0643 ** (2.22)	0.0652 ** (2.23)	FDI	0.2767 *** (6.13)	0.2181 *** (5.27)	0.2163 *** (4.91)
R^2	0.9217	0.9202	0.9201	R^2	0.7881	0.7901	0.7884
LM (error)	26.0660 ***	30.9490 ***	30.1150 ***	LM (error)	168.0420 ***	155.7740 ***	147.8290 ***
R-LM (error)	5.5850 **	7.2570 ***	7.1200 ***	R-LM (error)	27.5100 ***	24.9230 ***	19.7730 ***
LM (lag)	73.4610 ***	80.6140 ***	77.7810 ***	LM (lag)	261.8130 ***	240.4350 ***	256.4370 ***
R-LM (lag)	52.9800 ***	56.9220 ***	54.7860 ***	R-LM (lag)	121.2800 ***	109.5850 ***	128.3800 ***

Note: LM: Lagrange multiplier; R-LM: Robust Lagrange multiplier. *, **, *** indicate that they passed the significance test at the levels of 10%, 5%, and 1%.

The results in the table show that in the tests for spatial error and spatial lag, the assumption of "no spatial autocorrelation" was rejected, which indicates that a spatial econometric analysis should be performed. Comparing the Lagrange multiplier, it can be seen that the R-LM (lag) level of the SLM model is significantly higher than the R-LM (error) of the SEM model in the impact of technological capital investment on regional innovation output. We select the more significant SLM model for further analysis.

Before performing an SLM model analysis, a decision is needed on whether to use a fixed-effect or a random-effect model. In the choice between fixed effect and random effect models, combined with the LM test, the Hausman test, and Akaike information criterion (AIC) and Schwarz Criterion (SC) indicators, this paper selects the fixed effect model as the analysis model. Table 4 lists the estimation results of the SLM model under fixed effects.

Table 4. Results of the impact of regional allocation of technological resources on regional innovation.

Variables	CRDE	XRDE	YRDE	Variables	CRDP	XRDP	YRDP
CRDE	0.1750 *** (3.48)			CRDP	0.3449 *** (3.85)		
XRDE		0.0541 (1.42)		XRDP		−0.2055 ** (−2.44)	
YRDE			−0.01962 (−0.71)	YRDP			−0.1559 *** (−3.11)
RDE	1.0074 *** (60.88)	1.0175 *** (62.01)	1.0149 *** (59.96)	RDP	1.1591 *** (34.01)	1.1704 *** (32.91)	1.1748 *** (35.04)
WRDE	−0.5288 *** (−2.58)	−0.5392 *** (−2.61)	−0.5627 *** (−2.73)	WRDP	−0.5457 *** (−3.38)	−0.6535 *** (−3.63)	−0.5104 *** (−3.28)
FDI	0.0852 *** (3.21)	0.0634 ** (2.44)	0.0643 ** (2.47)	FDI	0.2470 *** (6.04)	0.1970 *** (5.02)	0.1936 *** (4.95)
ρ	0.07674 *** (4.10)	0.0810 *** (4.30)	0.0792 *** (4.19)	ρ	0.2756 *** (10.55)	0.2627 *** (9.70)	0.2695 *** (10.22)
R^2	0.8261	0.8137	0.8184	R^2	0.7880	0.7886	0.7880
Log L	−449.2385	−454.2231	−454.9762	Log L	−706.3906	−710.7528	−708.9141

Note: **, *** indicate that they passed the significance test at the levels of 5%, and 1%.

The results in the table show that the estimated coefficient of the CRDE variable is 0.1750, and it is significant at the level of 1%, which indicates that corporate technology capital expenditures have significantly promoted regional innovation growth, and the ratio of technological capital expenditures to total scientific and technological expenditures has increased by 1 percentage point. The corresponding innovation output increased by 0.1750 percentage points. The estimated coefficients of the XRDE and YRDE variables are not significant, indicating that the technological capital expenditures of universities and R&D institutions have not significantly affected the regional innovation output. On the whole, China's allocation of science and technology capital is not efficient, and the increase in science and technology capital expenditure of universities and R&D institutions cannot promote the growth of regional innovation output. Each year, China accounts for a certain percentage of funding in universities and R&D institutions, but this has the lowest innovation output. At the same time, it shows that the reason for the low innovation output of Chinese universities and R&D institutions is not the insufficient investment in science and technology capital, but the low level of organization and management of science and technology activities and the lack of effective operating mechanisms. Therefore, increasing the sci-tech capital investment of enterprises can promote the growth of regional innovation output.

Similar results are also shown for the input of scientific and technological personnel. The estimated coefficient of the CRDP variable is 0.3449, and it is significant at the level of 1%. This indicates that the investment of scientific and technological personnel of enterprises has significantly promoted the growth of regional innovation. The proportion was increased by 1 percentage point, and the regional innovation output was correspondingly increased by 0.3449 percentage points. The estimated coefficients of the XRDP and YRDP variables are significantly negative, which indicates that the increase in the number of scientific and technological personnel in universities and research institutions has not led to the growth of regional innovation output, but has inhibited the development of regional innovation output. This is mainly because the scientific research results of universities and research institutions appear in the form of a small number of patents, and the technologies that can generate patents are in the hands of a few teachers. The increase in the number of scientific and technological personnel alone cannot promote the growth of regional innovation output.

The possible reason for the above results is that this article selects the number of invention patent applications as a measure of regional innovation output. For universities and research institutions, the number of invention patent applications may not have been given much attention. Universities and research institutions attach more importance to basic research in the form of scientific papers and scientific works. They do not pay enough attention to invention patents and lack the ability to transform scientific research results into new technologies and products. Moreover, human capital is heterogeneous, and the increase in innovation output mainly depends on the promotion of a small number of core talents. The ineffective accumulation of research staff working hours will not have a positive impact on innovation output, which also reflects the importance of talent strategy for innovation development as well as the current low R&D efficiency and the need to optimize the performance evaluation of R&D personnel [42]. The above analysis shows that in the current context, to strengthen the status of enterprises as the mainstay of innovation, at the same time, it is necessary to increase the incentive policies of invention patents at universities and research institutions, promote their transformation of scientific research results into new technologies and new products, strengthen cooperation with enterprises, and promote the transfer and transformation of scientific and technological achievements. The government cannot simply invest science and technology resources in universities and research institutions. Instead, it should guide the formation of the industry–university-research cooperation model by adjusting the distribution of science and technology resources among different subjects. The investment in scientific and technological resources should be tilted towards enterprises, and at the same time, the ability of universities and research institutions to transform scientific and technological achievements should be improved.

Observing the estimation results of the three types of R&D entities, it can be seen that the corresponding coefficients of total scientific and technological capital expenditures, namely RDE, are 1.0074, 1.0175, and 1.0149, respectively, and they are all significantly positive. This shows that with the increase of China's investment in science and technology capital, the overall level of regional innovation output has shown an upward trend. In the SLM model, the ρ values were 0.07674, 0.0810, and 0.0792, and all passed the test at a significance level of 1%. This shows that regional innovation has a significant spatial spillover effect, and that the growth of regional innovation in neighboring regions in geographic space can drive regional innovation and development in the region. The coefficient of WRDE is significantly negative, which indicates that neighboring provinces' investment in science and technology capital in this province has restrained the increase of regional innovation output to a certain extent. This is mainly due to the increase in technology capital investment in neighboring provinces, which to some extent crowded out local technology capital investment. The promotion effect of local science and technology capital investment on innovation output is very significant. Due to the crowding out of science and technology capital investment in neighboring provinces, the level of innovation output in the province has been reduced.

On the whole, the effect of the allocation of scientific and technological personnel in the region on regional innovation is similar to the allocation of scientific and technological capital, which indicates that the estimation results of the allocation of scientific and technological resources in the region are robust. We consider the impact of three major R&D entities on regional innovation output. The impact of the investment in scientific and technological personnel of enterprises and the investment in scientific and technological capital on regional innovation output is similar, but the impact of scientific and technological personnel investment in higher education on regional innovation output is significantly negative. This shows that blindly increasing the proportion of scientific and technological personnel in institutions of higher education does not necessarily lead to an increase in innovation output. Cooperation with enterprises should be strengthened to transform the basic research results of institutions of higher education into applied research, thereby increasing the level of innovation output in local regions.

From the perspective of the overall impact of the scale of scientific and technological personnel's input on regional innovation output, the coefficients of scientific and technological personnel input from the three major R&D entities on regional innovation output are 1.1591, 1.1704, and 1.1748, which are significantly larger than the impact coefficient of scientific and technological capital input on regional innovation output, which indicates that the degree of influence of scientific and technological personnel investment on regional innovation output is significantly greater than that of technological capital investment on regional innovation output. From the results of the SLM model, it is known that the values of ρ are 0.2756, 0.2627, and 0.2695, respectively, indicating that there is a significant positive spatial correlation in regional innovation output. This spatial correlation feature relies mainly on the spatial transmission of the impact of errors. The WRDP coefficient is still significantly negative, that is, the input of scientific and technological personnel in neighboring provinces has a significant inhibitory effect on the development of regional innovation output in the province.

Since the setting of the spatial weight matrix may have a significant impact on the model estimation results, in order to test the robustness of the estimation results in Table 3, the spatial panel model is estimated based on the spatial weight matrix established by Equations (8) and (9).

The results obtained according to Equation (8) are shown in Table 5.

Table 5. Results of the impact of regional allocation of technological resources on regional innovation.

Variables	CRDE	XRDE	YRDE	Variables	CRDP	XRDP	YRDP
CRDE	0.1792 *** (3.54)			CRDP	0.3901 *** (4.41)		
XRDE		0.0465 (1.21)		XRDP		−0.1907 ** (−2.28)	
YRDE			−0.0124 (−0.44)	YRDP			−0.0930 * (−1.83)
RDE	1.0143 *** (61.06)	1.0253 *** (62.24)	1.0236 *** (60.72)	RDP	1.1558 *** (34.44)	1.1772 *** (33.49)	1.1946 *** (36.16)
WRDE	−0.5561 *** (−2.70)	−0.5727 *** (−2.75)	−0.5925 *** (−2.85)	WRDP	−0.6096 *** (−3.58)	−0.7108 *** (−3.79)	−0.6988 *** (−3.51)
FDI	0.0965 *** (3.59)	0.0748 *** (2.83)	0.0752 *** (2.85)	FDI	0.3057 *** (7.58)	0.2471 *** (6.35)	0.2469 *** (6.33)
ρ	0.0682 *** (2.99)	0.0557 *** (3.09)	0.0923 *** (2.98)	ρ	0.2674 *** (11.78)	0.2316 *** (10.72)	0.2474 *** (10.89)
R^2	0.9199	0.9183	0.9182	R^2	0.7374	0.7426	0.7400
Log L	−453.0874	−458.5554	−459.1919	Log L	−693.9786	−700.9625	−701.8900

Note: *, **, *** indicate that they passed the significance test at the levels of 10%, 5%, and 1%.

The results obtained according to Equation (9) are shown in Table 6.

Table 6. Results of the impact of regional allocation of technological resources on regional innovation.

Variables	CRDE	XRDE	YRDE	Variables	CRDP	XRDP	YRDP
CRDE	0.1734 *** (3.47)			CRDP	0.3184 *** (3.46)		
XRDE		0.0476 (1.26)		XRDP		−0.3072 ** (−3.66)	
YRDE			−0.0168 (−0.61)	YRDP			−0.1629 *** (−3.17)
RDE	1.0182 *** (65.35)	1.0292 *** (66.87)	1.0266 *** (64.23)	RDP	1.2221 *** (35.70)	1.2046 *** (33.47)	1.2306 *** (36.51)
WRDE	−0.5472 *** (−2.70)	−0.5622 *** (−2.74)	−0.5819 *** (−2.84)	WRDP	−0.6659 *** (−2.86)	−0.8067 *** (−2.98)	−0.6236 *** (−3.53)
FDI	0.0996 *** (3.77)	0.0786 *** (3.03)	0.0792 *** (3.05)	FDI	0.2930 *** (6.99)	0.2431 *** (6.08)	0.2421 *** (6.04)
ρ	0.0069 *** (5.08)	0.0193 *** (5.20)	0.0069 *** (5.14)	ρ	0.0631 *** (9.13)	0.0549 *** (8.86)	0.0310 *** (8.97)
R^2	0.8753	0.8707	0.8714	R^2	0.4297	0.4489	0.4384
Log L	−444.8956	−450.0707	−450.6726	Log L	−717.2743	−716.5777	−718.1894

Note: **, *** indicate that they passed the significance test at the levels of 5%, and 1%.

As apparent from Tables 5 and 6, the estimation results of this kind of spatial weight matrix basically show a consistent phenomenon, which indicates that the estimation results of the fixed-effect space lag model are robust.

5.2. Inter-Regional Spatial Econometric Analysis Results

The flow of science and technology resources between different provinces has realized the reallocation of science and technology resources in space, which has a two-sided effect on changes in regional innovation output. On the one hand, for the sake of profitability, science and technology resources tend to flow into provinces with higher levels of regional innovation output, making the allocation of science and technology resources more efficient in space. In addition, during the flow of scientific and technological capital and personnel, relevant technical knowledge will be carried, which will speed up the dissemination of technical knowledge, thereby promoting the growth of regional innovation output. On the other hand, the flow of scientific and technological resources will cause a shortage of resources out of the provinces and the overcrowded use of infrastructure in the provinces, which will inhibit the development of regional innovation. Whether scientific and technological resource flow is favorable or unfavorable to regional innovation output is the focus of this article. Table 7 shows the specific impact of the cross-regional flow of technological capital and scientific and technological personnel of enterprises, universities, and research institutions on regional innovation output.

Table 7. Results of the impact of regional allocation of technological resources on regional innovation.

Variables	CRDE	XRDE	YRDE	Variables	XRDP	XRDP	YRDP
CRDE	0.0695 *** (2.53)			CRDP	0.2732 *** (3.20)		
XRDE		0.1749 *** (5.17)		XRDP		−0.1790 ** (−2.18)	
YRDE			−0.0279 (−1.10)	YRDP			−0.0645 *** (−3.24)
RDE	0.8145 *** (2.84)	0.8255 *** (3.31)	0.7369 *** (3.37)	RDP	0.6206 *** (2.43)	0.7105 *** (4.63)	0.5912 (0.75)
WRDE	−0.1910 *** (−2.71)	−0.1971 *** (−3.98)	−0.1717 *** (−2.73)	WRDP	−0.2543 *** (−2.76)	−0.1381*** (−3.02)	−0.2096 *** (−2.98)
FRDE	0.0127 *** (2.60)	0.0262 *** (4.28)	0.0384 *** (3.08)	FRDP	0.0353 *** (3.10)	0.0551 *** (2.82)	0.0959 *** (3.50)
FDI	0.1167 *** (5.65)	0.1171 *** (5.79)	0.1199 *** (5.74)	FDI	0.3366 *** (9.53)	0.3366 *** (9.48)	0.3207 *** (8.80)
ρ	0.4362 *** (34.64)	0.4277 *** (34.64)	0.4367 *** (34.64)	ρ	0.7748 *** (34.64)	0.7789 *** (34.57)	0.7804 *** (34.55)
R^2	0.6922	0.9457	0.9437	R^2	0.8254	0.8231	0.8228
Log L	−353.6240	−341.7460	−354.1960	Log L	−698.2620	−701.4640	−702.5970

Note: **, *** indicate that they passed the significance test at the levels of 5%, and 1%.

It can be seen from Table 7 that in the econometric model, the influence coefficient signs of the inter-regional flow variable FRDE of scientific and technological capital and the inter-regional flow variable FRDP of scientific and technological personnel are positive and pass the significance level test. This indicates the inter-regional flow of scientific and technological resources. It has a significant promotion effect on regional innovation output growth. As to technological capital and personnel as innovation factors, their interregional flows have increased the economic scale of each technology in each region. At the same time, the expansion of the flow of science and technology resources across regions has increased the degree of regional economic integration. The increasing effect of scale returns brought about by the spread of knowledge and technology and economic integration will eventually increase the level of innovation output in various regions and nations. Comparing the regression coefficient values of the two types of resource flows, it can be seen that the effect of unit scientific and technological personnel mobility on regional innovation output is higher than the effect of unit technological capital flow between regions.

Therefore, removing the institutional barriers that restrict the flow of scientific and technological personnel and fully realizing the resource reallocation effect brought by the flow of research and development personnel has a very important role in accelerating the improvement of regional innovation output. In addition, the regression results of the allocation structure of each innovation subject in the science and technology resource area are basically consistent with Table 4 except XRDE. The sign and significance level of the estimated coefficients of each variable are basically consistent, which also proves to a certain extent that the estimation results of this paper are robust. After considering inter-regional mobility, the coefficient of XRDE has changed from insignificant to significant, which indicates that the flow of scientific and technological personnel between colleges and universities in different provinces can significantly promote regional innovation output.

In order to test the robustness of the estimation results in Table 7, the spatial panel model estimation is performed according to the spatial weight matrix established by Equations (8) and (9). The estimation results of the three spatial weight matrices are basically consistent, which indicates that the estimation results of the fixed-effect space lag model are robust.

6. Discussion

In recent years, China's economy has grown rapidly, and the growth rate in the input of science and technology resources has become increasingly apparent. Behind the increase in investment in scientific and technological resources, we need to be more aware of the impact of the allocation of scientific and technological resources on regional innovation output. This paper uses the panel data of 30 provinces in China from 1998 to 2017 to construct a regional innovation output growth model that includes both scientific and technological resource inputs and allocation of scientific and technological resources and uses space econometric models to empirically examine the specific effects of the input and allocation of scientific and technological resources on regional innovation output.

(1) China's regional innovation output and scientific and technological resource input show obvious agglomeration characteristics in space, mainly manifested in positive spatial correlation; that is, provinces with higher innovation intensity tend to be closer to other provinces with higher innovation intensity. The spatial correlation test shows that the economically developed areas along the eastern coast of China basically show H–H spatial correlation patterns. The L–L spatial correlation model basically belongs to the underdeveloped western regions. The central region is in the east–west connection region, and it is generally in the H–L and L–H spatial correlation patterns. The emergence of this association pattern indicates that apart from China's uneven distribution of scientific and technological resources, it also has the characteristics of spatial dependence. In other words, the level of development of innovation output in each province is not only affected by the input of science and technology resources in this province, but also by the input of science and technology resources and innovation output in neighboring provinces. Therefore, when the state supports innovation development in the west, it also needs to pay attention to the spatial relationship between innovation output and the input of scientific and technological resources, and try to avoid suppressing innovation output.

(2) The efficiency of scientific and technological resource input by application-oriented research entities that are mainly enterprises is higher, and the promotion of regional innovation output is more significant. The investment in scientific and technological capital of universities and research institutions is not significant, and the input of scientific and technological personnel is significantly negative. The emergence of this phenomenon indicates that universities and research institutions need to pay more attention to invention patents and lack the ability to transform scientific research results into new technologies or new products. Human capital itself is heterogeneous. Innovation output depends mainly on a small number of core talents. Ineffective accumulation of working hours of scientific

researchers will not promote innovation output. In general, the input of scientific and technological resources has a significant role in promoting regional innovation output, and the degree of impact of scientific and technological personnel input on regional innovation output is significantly greater than the effect of scientific and technological capital input on regional innovation. The emergence of this phenomenon indicates that under the fixed circumstances of the innovation environment, increasing the input of scientific and technological personnel is more significant in promoting regional innovation output than increasing the input of scientific and technological capital in the same proportion. Therefore, in the allocation of scientific and technological resources, attention should be paid to applied research areas with greater innovation output intensity, increasing the proportion of enterprises' scientific and technological resources investment, increasing the input of scientific and technological personnel in applied research fields, strengthening the level of transformation of basic research into applied research by universities and research institutions, strengthening cooperation between industry, universities, and research institutions, and promoting the development of regional innovation output levels.

(3) The input of science and technology resources in neighboring provinces will have a significant inhibitory effect on the innovation output of the province, and this inhibitory effect is reflected in the input of scientific and technological capital and the input of scientific and technological personnel. The emergence of this situation indicates that the province's innovation output cannot depend on the input of science and technology resources in other provinces. In the allocation of scientific and technological resources, we should give full play to the advantages of local resources, strengthen investment in scientific and technological resources in the province, increase the flow of scientific and technological capital and the introduction of scientific and technological personnel, and enhance the inherent motivation for innovation.

(4) In the case of interregional mobility, the signs of the influence coefficients of the interregional mobility variables of scientific and technological resources are significantly positive, reflecting that the regional mobility of scientific and technological resources has a significant promotion effect on the growth of regional innovation output. The promotion effect of innovation output is superior to the promotion effect of technological capital flow on regional innovation output. Therefore, when raising the level of regional innovation output, we should eliminate the institutional barriers that restrict the flow of scientific and technological resources, strengthen the level of cooperation between enterprise, universities, and research institutions, promote the flow of scientific and technological resources between enterprises, universities, and research institutions, and establish a long-term mechanism for collaborative innovation, to achieve coordinated development of regional innovation.

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