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Research Article

Quantitative Impact Analysis of Financial Support on Regional Science and Technology Innovation and Productivity Based on the Multivariate Statistical Model

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Science and technology (S&T) innovation is a significant driving force for regional productivity, and strong financial support can effectively promote S&T innovation. As the regional main body of S&T innovation, the first thing that enterprises need to address is the demand for funds. Internal funds are needed to maintain the overall daily operation of enterprises, and regional science and technology innovation funds mainly come from external financial support. Using the factor analysis method, multiple indicators were adopted to comprehensively evaluate the level of S&T innovation in each province and city as the variables and financial scale, financial structure, and financial efficiency as the variables, and the impact of financial support on science and technology innovation in four major regions was empirically studied using a panel data model. The degree of development of banking institutions and capital markets in different regions of China varies, and the financial system's support for China's S&T innovation varies widely. Therefore, it is important to study the impact of financial support on science and technology innovation among different regions in China for the balanced development of China's regions.

1. Introduction

S&T innovation is the primary driving force for development and an important driving force for economic growth and structural optimization. The relationship between finance and S&T innovation is very close; as an important force supporting the development of S&T innovation, finance can not only provide financial support but also help disperse the risks in the process of innovation. At the same time, scientific and technological innovation brings about the innovation of tools, which leads to a high production efficiency [1–4]. As for the influence of finance on scientific and technological innovation, most scholars believe that financial development can promote scientific and technological innovation. For example, Chowdhury et al. collected relevant data from developed and emerging countries and believed that the development of the financial market is conducive to improving the efficiency of enterprises' research and development (R&D) investment. Maskus et al. took the relevant data of 18 OECD countries from 1990 to 2003 as samples to study the influence of domestic and international financial market development on their manufacturing R&D intensity, and the results showed that the diversity of financial development forms was an important factor determining R&D intensity. In addition, the degree of financial development has a different impact on technological innovation. The study found that countries with a high level of financial development had little positive effect of financial development on technological innovation. Middle-level countries have a greater positive effect on S&T innovation. However, in countries with a low level of financial development, its impact on S&T innovation is uncertain. [5, 6].

Finance plays a significant role in promoting S&T innovation. Sun et al. [7] believe that at the national level, financial development plays an increasingly important role in technological innovation. From the regional point of view, financial development promotes technological innovation in China's provinces and regions with efficiency and consistency. Zhang et al. [8] studied the impact of finance on regional S&T innovative enterprises by taking 559 S&T innovative listed companies in 30 provinces and regions of China as examples and found that finance has a significant positive impact on regional S&T innovative enterprises. Financial development can provide more financing convenience and guarantee for enterprises, thus promoting the efficiency of innovation-oriented enterprises. Du et al. [9] also believe that finance can significantly promote the improvement of regional innovation ability, and this influence also has a spillover effect in space. Sun et al. [10] refined financial development indicators and analyzed the mechanism of financial development on technological innovation from the aspects of development scale, structure, and financial ecological environment. The effect of finance on S&T innovation is a double-edged sword, and finance can positively promote S&T innovation through credit constraint easing effect, resource allocation effect, external scale effect, and reverse crowding-out effect through excessive competition effect and cost effect [1, 11–15]. Whether the agglomeration of the financial industry has a positive or negative impact on S&T innovation depends on the relative magnitude of its positive promotion and reverse extrusion. On the one hand, for carrying out scientific and technological innovation activities, one needs to invest a large amount of capital, while financial agglomeration can solve the financing problem of capital demand by gathering idle social funds and investing them in scientific and technological innovation projects [16–20]. On the other hand, the risk dispersion function of financial agglomeration can help alleviate the uncertainty in the R&D process of scientific and technological innovation projects. The second is the information spillover effect. Financial agglomeration strengthens information sharing between financial institutions and enterprises, effectively avoids adverse selection through the full exchange of financial information between transaction parties, and promotes the improvement of technological innovation efficiency of enterprises through the information spillover effect. The third is the economies of scale [21–27]. The integration and convergence of huge financial resources in a specific region and the complementarity and innovation of various resources will produce an obvious "scale effect." Financial agglomeration improves the efficiency of scientific and technological innovation by providing investment and financing facilities for innovative enterprises, reducing their financing costs and risks, thus accelerating the capital flow of enterprises. In addition, financial agglomeration accelerates the diffusion of core technologies and knowledge, which will also promote the improvement of the technological innovation level. [28–33].

Based on the financial support of the multivariate statistical model, this article analyzes and studies the regional S&T innovation and its production efficiency, further explores the impact of financial support on regional development, and uses scientific methods to reflect the comprehensive strength of the region.

2. Multivariate Statistical Model

2.1. Principal Component Analysis. Principal component analysis is a method of condensing data information from many indicators into composite indicators (principal components) and ensuring that these composite indicators are independent of each other. In the study of practical problems, in order to reduce the difficulty of analysis and improve the efficiency of analysis, the m-dimensional random vector X=(x1, x2, ... xm), but the first linear transformation of X transforms the original m-dimensional random vector into a new comprehensive variable L1, L2, ... Lm.

$$\begin{aligned} \mu &= E(X), \\ \sum &= D(X). \end{aligned} \tag{1}$$

Taking the linear transformation of X, we get

$$\begin{cases} Y_1 = t_{11}X_1 + t_{12}X_2 + \cdots + t_{1p}X_p = T_1X \\ Y_2 = t_{21}X_1 + t_{22}X_2 + \cdots + t_{2p}X_p = T_2X \\ \vdots \\ Y_p = t_{p1}X_1 + t_{p2}X_2 + \cdots + t_{pp}X_p = T_pX \end{cases}. \tag{2}$$

Let $Y = T'X$, where $Y = (Y_1, Y_2..., Y_p)$ and $T = (T_1, T_2..., T_p)$.

$Y_1, Y_2, ..., Y_n$ $(n< P)$ are obtained by conversion, and these are independent of each other.

$$D(Y_i) = D(T_i'X) = T_i'D(X)T_i'' = T_i' \sum T_i, i = 1, 2, \ldots, n. \tag{3}$$

In order for $Y_1, Y_2, ..., Y_n$ $(n < P)$ to fully reflect the information of the original variables, it is required that T_i maximizes $D(Y_i) = T_i' \sum T_i$. Assuming that T_i satisfies $T_i'T_i = 1$, or $|T| = 1$, the unbounded increase of $D(Y_i)$ due to multiplying T_i by any of the constants is eliminated:

The first principal component Y_1 satisfies $Y_1 = T_1'X$, where $T_1'T_1 = 1$ and $D(Y_1) = T_1' \sum T_1$ reaches its maximum value

The second principal component Y_2 satisfies $Y_2 = T_2'X$, where $T_2'T_2 = 1$ and $D(Y_2) = T_2' \sum T_2$ reaches its maximum value

The *k-th* principal component Y_2 satisfies $Y_k = T_k'X$, where $T_k'T_k = 1$ and $D(Y_k) = T_k' \sum T_k$ reaches its maximum value

To find the first component, the objective function is constructed as follows:

$$\varphi_1(T_1, \lambda) = T_1' \sum T_1 - \lambda(T_1'T_1) - 1, \tag{4}$$

$$\frac{\partial \varphi_1}{\partial T_1} = 2 \sum T_1 - 2\lambda T_1 = 0, \tag{5}$$

$$\left(\sum - \lambda I\right)T_1 = 0, \tag{6}$$

$$T_1' \sum T_1 = \lambda. \tag{7}$$

The covariance array $\sum$ of X is a nonnegative definite, assuming that the roots of equation (6) are λ_i, and $\lambda_1 \geqq \lambda_2 \geqq \ldots \geqq \lambda_p \geqq 0$, where $i = 1, 2, \ldots, p$. The variance of Y_1 is λ_1 from equation (7); then, the maximum variance of Y_1 is λ_1, and the corresponding unitized eigenvector is T_1.

Transforming equation (5) yields $T_2' \sum T_1 = \lambda T_2'$. Since Y_1 and Y_2 are independent of each other, we have $T_2' T_1 = 0$ or $T_1' T_2 = 0$. The objective function of the second principal component is given by the following equation:

$$\varphi_2(T_2, \lambda, \rho) = T_2' \sum T_2 - \lambda(T_2' T_2 - 1) - 2\rho(T_1' T_2), \tag{8}$$

$$\frac{\partial \varphi_2}{\partial T_2} = 2 \sum T_2 - 2\lambda T_2 - 2\rho T_1 = 0, \tag{9}$$

$$T_1' \sum T_2 - \lambda T_1' T_2 - \rho T_1' T_1 = 0, \tag{10}$$

$$\left(\sum - \lambda I\right) T_2 = 0, \tag{11}$$

$$T_2' \sum T_2 = \lambda. \tag{12}$$

The covariance array $\sum$ of X is a nonnegative definite, assuming that the roots of equation (11) are λ_i, and $\lambda_1 \geqq \lambda_2 \geqq \ldots \geqq \lambda_p \geqq 0$, where $i = 1, 2, \ldots, p$. The variance of Y_2 is λ_2 from equation (12); then, the maximum variance of Y_2 is λ_2, and the corresponding unitized eigenvector is T_2.

The k-th principal component Y_k satisfies $Y_k = T_k' X$, where $T_k' T_i = 1$ and $T_k' T_i = 0$ $(i \leqq k)$, and $D(Y_k) = T_k' \sum T_k$ reaches the maximum. The construction objective function of the k-th principal component is as follows:

$$\varphi_k(T_k, \lambda, \rho) = T_k' \sum T_k - \lambda(T_k' T_k - 1) - 2\sum_{i=1}^{k-1} \rho_i (T_i' T_k), \tag{13}$$

$$\frac{\partial \varphi_k}{\partial T_k} = 2 \sum T_k - 2\lambda T_k - 2\sum_{i=1}^{k-1} \rho_i T_i = 0, \tag{14}$$

$$T_i' \sum T_k - \lambda T_i' T_k - T_i' \left(\sum_{i=1}^{k-1} \rho_i T_i \right) = 0, \tag{15}$$

$$\left(\sum - \lambda I\right) T_k = 0, \tag{16}$$

$$T_k' \sum T_k = \lambda. \tag{17}$$

The covariance array $\sum$ of X is a nonnegative definite, assuming that the roots of equation (15) are λ_i, and $\lambda_1 \geqq \lambda_2 \geqq \ldots \geqq \lambda_p \geqq 0$, where $i = 1, 2, \ldots, p$. The variance of Y_k is λ_k from equation (16); then, the maximum variance of Y_k is λ_k, and the unitized eigenvector is T_k. The calculation steps of principal components are shown in Figure 1.

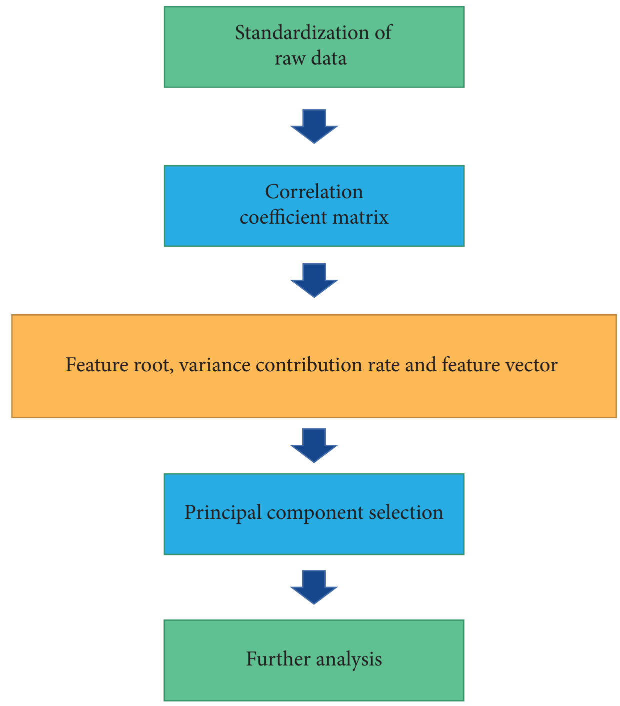

FIGURE 1: Calculation steps of principal components.

2.2. Factor Analysis. The basic purpose of factor analysis is to use a few factors to describe the relationship between many indicators or factors; that is, several closely related variables are grouped in the same category, each category of variables becomes a factor, and a few factors reflect most of the information of the original data. It is used to describe some of the more basic but not directly measurable variables hidden in a set of directly measurable variables. Using the idea of dimensionality reduction, starting from the intrinsic correlation of the original variable correlation matrix, the essence of the same variable is reduced to a factor, so as to achieve the purpose of dimensionality reduction.

We assume that there are n samples, and each sample has p indicators with a strong correlation among these p indicators. We then standardize the original data, use $X=(X_1, X_2, \ldots, X_p)$ to represent the standardized variable, and use $F_1, F_2, \ldots\ldots,$ and F_m $(m < p)$ to represent the common factor, and E is the special factor of X_i $(i = 1, 2, \ldots\ldots, p)$.

(1) $X=(X_1, X_2, \ldots\ldots, X_p)$ is a p-dimensional random variable, the mean vector $E(X) = 0$, covariance matrix

$cov(X) = \sum$, and covariance matrix is equal to correlation matrix R.

(2) F=($F1$, $F2$, ..., Fm) ($m < p$) is not observable, the mean vector $E(F) = 0$, and covariance matrix $\text{cov}(F) = 1$, where F1, F2, ..., Fm are mutually independent and the variance is 1.

(3) F and $\mathcal{E} = (\varepsilon_1, \varepsilon_2..., \varepsilon_p)$ are independent variables, where the mean vector $E(\varepsilon) = 0$ and the covariance matrix $\sum\varepsilon$ is a diagonal matrix, denoted as follows:

$$\text{cov}(\varepsilon) = \sum_{\varepsilon} = \begin{bmatrix} \sigma_{11}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{22}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{pp}^2 \end{bmatrix}. \tag{18}$$

$\varepsilon_1, \varepsilon_2..., \varepsilon_p$ are also independent, but the variances do not have to be equal.

(4) $cov(\text{F}, \varepsilon) = 0$; that is,

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1p}F_p + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2p}F_p + \varepsilon_2 \\ \cdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pp}F_p + \varepsilon_p \end{cases},$$
$$X = AF + \varepsilon, \tag{19}$$
$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pp} \end{bmatrix}.$$

A is the factor load matrix, a_{ij} is the factor load, and A represents the load of the ith variable on the j-th factor.

The codegree considers the relationship between all the common factors $F1$, $F2$, ..., Fm and one of the original variables and calls $a_{i1}^2 + a_{i2}^2 + \cdots + a_{im}^2$ the codegree of Xi, denoted as $h_i^2\,(i = 1, 2, \ldots, p)$. The following equation can be obtained by the premise of the factor model:

$$\begin{aligned} D(X_i) &= h_i^2 + D(\varepsilon_i), \\ D(X_i) &= h_i^2 + \sigma_i^2. \end{aligned} \tag{20}$$

The coefficient h_i^2 is complementary to the residual variance σ_i^2.

Placing the p principal components in the order from the largest to the smallest, they are written as Y_1, Y_2, ..., Y_p in order; then, the relationship between the principal components and the original variables is as follows:

$$\begin{cases} Y_1 = t_{11}X_1 + t_{12}X_2 + \cdots + t_{1P}X_P \\ Y_2 = t_{21}X_1 + t_{22}X_2 + \cdots + t_{2P}X_P \\ \vdots \\ Y_P = t_{P1}X_1 + t_{P2}X_2 + \cdots + t_{PP}X_P \end{cases}, \tag{21}$$

where t_{ij} is the component of the feature vector. The equation of the relation from Y transformed into X is as follows:

$$\begin{cases} X_1 = t_{11}Y_1 + t_{21}Y_2 + \cdots + t_{P1}Y_P \\ X_2 = t_{12}Y_1 + t_{22}Y_2 + \cdots + t_{P2}Y_P \\ \vdots \\ X_P = t_{1P}Y_1 + t_{2P}Y_2 + \cdots + t_{PP}Y_P \end{cases},$$
$$\begin{cases} X_1 = t_{11}Y_1 + t_{21}Y_2 + \cdots + t_{m1}Y_m + \varepsilon_1 \\ X_2 = t_{12}Y_1 + t_{22}Y_2 + \cdots + t_{m2}Y_m + \varepsilon_2 \\ \vdots \\ X_P = t_{1P}Y_1 + t_{2P}Y_2 + \cdots + t_{mp}Y_m + \varepsilon_p \end{cases} \tag{22}$$

Since the principal components Yi are uncorrelated with each other, transforming the principal components Yi into variables with variance 1 makes the principal components become a common factor.

$$\begin{cases} X_1 = a_{11}F_1 + t_{12}F_2 + \cdots + t_{1m}F_m + \varepsilon_1 \\ X_2 = a_{21}F_1 + t_{22}F_2 + \cdots + t_{2m}F_m + \varepsilon_2 \\ \vdots \\ X_P = a_{P1}F_1 + t_{P2}F_2 + \cdots + t_{mp}F_m + \varepsilon_p \end{cases}. \tag{23}$$

Suppose $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_p$ are the eigenvalues and their corresponding standard orthogonal eigenvectors are T_1, T_2, ..., T_p. Since $m \leq p$, the solution set of the load matrix A is given by the following equation:

$$\begin{aligned} A &= \left(\sqrt{\lambda_1}\,t_1, \sqrt{\lambda_2}\,t_2, \ldots, \sqrt{\lambda_m}\,t_m\right), \\ h_i^2 &= a_{i1}^2 + a_{i2}^2 + \cdots + a_{im}^2, i = 1, 2, \ldots, p. \end{aligned} \tag{24}$$

The load matrix A is multiplied by the orthogonal array K to give the factor orthogonal rotation. The factor loading matrix after rotation is A', which gives the following equation:

$$A' = AK = \left(a_{ij}'\right)_{p\times m}, \tag{25}$$

$$d_{ij} = \frac{a_{ij}'}{h_j}, \tag{26}$$

$$\overline{d}_j = \frac{1}{p}\sum_{i=1}^{p} d_{ij}^2. \tag{27}$$

The relative squared difference of the elements in the first column of A' can be defined as W_j.

$$W_j = \frac{1}{p}\sum_{i=1}^{p}\left(d_{ij}^2 - \overline{d}_j\right)^2. \tag{28}$$

We used the Thomson regression method to calculate the factor scores. The regression equation is

$$F_j' = b_{j0} + b_{j1}X_1 + \cdots + b_{jp}X_p, j = 1, 2, \ldots, m. \tag{29}$$

According to the statistical significance equation (27) of factor load AIj, it can be seen that for any $i = 1, 2, ..., p$ and $j = 1, 2, ..., m$,

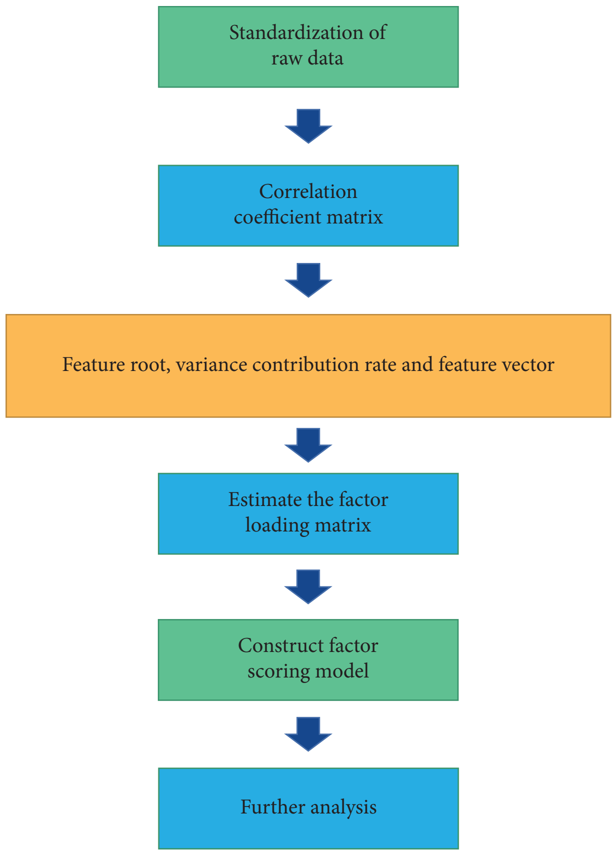

Figure 2: Steps of factor analysis.

$$\begin{aligned} a_{ij} &= r_{x_i,F_j} \\ &= E\left[X_i\left(b_{j1}X_1 + b_{j2}X_2 + \cdots + b_{jp}X_p\right)\right] \\ &= b_{j1}r_{i1} + b_{j2}r_{i2} + \cdots + b_{jp}r_{ip}, \\ B &= \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mp} \end{bmatrix}, \\ A &= RB', B = A'R^{-1}, \end{aligned} \quad (30)$$

where R is the coefficient matrix and A is the load matrix; then, the factor scoring formula can be calculated as

$$F' = \begin{bmatrix} F_1' \\ F_2' \\ \vdots \\ F_m' \end{bmatrix} = \begin{bmatrix} b_1'X \\ b_2'X \\ \vdots \\ b_m'X \end{bmatrix} = BX = A'R^{-1}X. \quad (31)$$

The steps of factor analysis are shown in Figure 2.

3. Regional Development Analysis of Financial Support

3.1. Evaluation and Analysis of the S&T Innovation Level. The investment in S&T innovation includes human and capital investment. R&D activities require the application of scientific methods to create new knowledge or create new applications. The scale and intensity of R&D activities can reflect the S&T strength of a region, so the budgeted R&D personnel and R&D expenses are used as variables, and the proportion of local government S&T expenditures to local fiscal expenditures reflects the local government's funding for S&T innovation. The output of S&T innovation includes patent output and product output. Patent output includes the number of patent applications and the number of patents granted. A technology market is a place for the exchange of commodity technology results, and the turnover of the technology market refers to the total amount of the subject matter of technology contracts. New product sales revenue refers to the sales revenue achieved through the sale of new products (products manufactured using new technology principles or new design concepts).

China's financial industry supports technological innovation from three aspects: banking institutions, general capital market, and venture capital. However, due to the direct and obvious effect of venture capital on high-tech enterprises and the late start of venture capital in China, the relevant data statistics of various provinces and cities are not standardized and perfect. In view of the reality and availability of data, this article studies the financial support of regional S&T innovation in China from two aspects, that is, banking and the capital market. Furthermore, in order to reflect the financial structure, deepen the longitudinal and transverse wide degree, and, at the same time, show the level of financial industry overall development impact on scientific and technological innovation, this article does not directly select banking institutions and capital market as a financial variables, but, in reference on the basis of domestic and foreign scholars' study, selects financial scale, financial structure, and financial efficiency as indicators to measure the level of financial development.

The focus of this study is to analyze the financial structure and its changes. The financial correlation ratio can better measure the degree of financial deepening, so the index of the financial correlation ratio is selected to represent the financial scale. The total value of financial assets includes money supply, stock market value, and bond balance. The sources of financial assets related to enterprise scientific and technological innovation mainly include indirect financing dominated by bank loans and direct financing represented by the capital market. Considering data availability and representativeness, the calculation method of financial scale is as follows:

$$\text{FSC} = \frac{\text{total bank loans} + \text{total stock market value}}{\text{GDP}}. \quad (32)$$

Financial structure: the financing of Chinese enterprises' S&T innovation comes from the banking industry and the

Table 1: Total variance.

	Total	Initial eigenvalue		Extraction of the sum of squares and load			Rotation of squares and load		
		Variance %	Accumulate %	Total	Variance %	Accumulate %	Total	Variance %	Accumulate %
1	4.38	71.16	71.16	5.25	71.16	71.16	3.98	63.65	63.65
2	2.42	21.74	92.90	1.45	21.74	92.90	2.73	29.26	92.90
3	0.33	0.83	95.81						
4	0.12	0.83	94.99						
5	0.02	0.21	96.10						
6	0.005	0.07	96.72						
7	0.001	0.02	100						

Table 2: The factor loading matrix and factor score matrix table.

	Factor load matrix		Rotation factor load matrix		Factor scoring coefficient matrix	
	1	2	1	2	1	2
X1	0.956	−0.120	0.926	0.268	0.194	−0.004
X2	0.951	−0.163	0.937	0.227	0.203	−0.030
X3	0.590	0.758	0.242	0.929	−0.100	0.507
X4	0.956	−0.147	0.936	0.242	0.201	−0.020
X5	0.930	−0.242	0.951	0.145	0.221	−0.080
X6	0.520	0.807	0.158	0.948	−0.125	0.532
X7	0.934	−0.248	0.956	0.141	0.224	−0.084

Table 3: Technological innovation level of a province in 14 years.

Year	F_1	F_2	STI
1	0.287	−0.467	0.069
2	0.267	−0.431	0.066
3	0.267	−0.431	0.071
4	0.271	−0.437	0.082
5	0.296	−0.481	0.087
6	0.298	−0.485	0.095
7	0.292	−0.474	0.096
8	0.313	−0.511	0.108
9	0.308	−0.503	0.113
10	0.315	−0.514	0.108
11	0.313	−0.512	0.116
12	0.346	−0.570	0.126
13	0.356	−0.587	0.127
14	0.373	−0.618	0.133
15	0.388	−0.639	0.134

financial market. The rapid development of the security market in recent years highlights the changes in the financial structure and reflects the degree of financial globalization. Therefore, the total market value of stocks represents the financing method of the security market, and the variable of financial structure FST = the total market value of stocks/total bank loans. The larger the value is, the greater the support of the capital market for S&T innovation is. Financial efficiency: the function of the financial system is to centralize and redistribute capital, and the efficiency of capital distribution is directly related to the use of capital. In China's financial system, banks account for a large proportion. This article studies the conversion efficiency of banking institutions between deposits and loans from the perspective of financial intermediation. FEF = total bank loans/total bank deposits. The higher the conversion efficiency is, the more active the financial intermediary and the greater the support for S&T innovation are.

Before the comprehensive evaluation of the scientific and technological innovation level, the data collected from 31 regions in Mainland China for 14 years are standardized according to the method introduced above, so as to eliminate the differences caused by different dimensions of variables, and then, the factor analysis is carried out. As there are many provinces which are being studied, the calculation process is not listed one by one. A province is taken as an example to illustrate the factor analysis process of a comprehensive evaluation of scientific and technological innovation levels. In the adaptability test of factor analysis, the KMO value obtained is 0.835, and the significance level of the Bartlett sphericity test is $P = 0.00$. The null hypothesis is that variables that cannot correlate are rejected, and it can be considered that there is a strong correlation between these seven variables, which is suitable for factor analysis. Therefore, the total variance of interpretation can be obtained through software operation, and the number of extracted factors can be determined. The details are listed in Table 1.

As can be seen from Table 1, the eigenvalues of the first two factors are greater than 1, and the cumulative variance contribution rate reaches 92.90%. Selecting the first two factors can better reflect the original data information. F_1 and F_2 are used to represent the selected factors, and the factor load matrix and the factor score coefficient matrix can be obtained to describe the composition of the two principal components, as shown in Table 2.

The rotated factor load matrix more clearly describes the classification of factors. As can be seen from the table, the main factor F_1 mainly explains five variables including the number of R&D personnel, internal expenditure of R&D funds, patent applications, patent grants, and sales revenue of new products. The main factor F_2 mainly explains two variables: the proportion of science and technology expenditure in local financial expenditure and the turnover of the technology market. According to the common factor score coefficient matrix analyzed by the software, the scores of the two factors in each year are calculated, and then, the extracted variance contribution rate is weighted to each factor to obtain the comprehensive score STI of each year.

Table 4: Unit root test results.

Area	Inspection methods	Original sequence		Difference of first order	
		t	Probability	T	Probability
Eastern region	ADF-Choi Z-stat	−0.642	0.246	−6.440	0.000
	PP-Choi Z-stat	−1.420	0.069	−7.091	0.000
	Levin, Lin, and Chut	−2.455	0.019	−9.938	0.000
	Im, Pesaran, and Shin W-stat	−0.626	0.251	−7.140	0.000
Central region	ADF-Choi Z-stat	2.930	0.968	−2.281	0.009
	PP-Choi Z-stat	2.361	0.962	−2.811	0.002
	Levin, Lin and Chut	2.153	0.956	−4.994	0.000
	Im, Pesaran, and Shin W-stat	3.455	0.969	−2.778	0.002
Western region	ADF-Choi Z-stat	2.771	0.967	−4.136	0.000
	PP-Choi Z-stat	3.545	0.969	−4.666	0.000
	Levin, Lin, and Chut	1.113	0.848	−6.367	0.000
	Im, Pesaran, and Shin W-stat	2.754	0.967	−4.311	0.000
Northeast region	ADF-Choi Z-stat	2.038	0.952	−1.321	0.084
	PP-Choi Z-stat	2.988	0.968	−2.276	0.009
	Levin, Lin, and Chut	0.549	0.692	−3.313	0.000
	Im, Pesaran, and Shin W-stat	1.944	0.947	−1.393	0.073

$$\begin{aligned} F_1 &= 0.194X_1 + 0.203X_2 - 0.1X_3 + 0.201X_4 + 0.221X_5 \\ &\quad - 0.125X_6 + 0.224X_7, \\ F_2 &= -0.004X_1 - 0.03X_2 + 0.507X_3 - 0.20X_4 \\ &\quad - 0.08X_5 + 0.532X_6 - 0.084X_7. \end{aligned} \tag{33}$$

Among them, X_1, X_2,..., X_7 are the standardized data of each variable after processing. The comprehensive score $\mathrm{STI} = (F_1 * 63.65 + F_2 * 29.26)/92.90$ was calculated.

From the result of factor analysis, it can be seen that the comprehensive level of scientific and technological innovation of all regions in China in 14 years shows an overall upward trend, and it fluctuates slightly in the second and fifth years, basically showing strong S&T innovation ability. From the comparison between provinces and cities, Guangdong province has the highest level of S&T innovation, followed by Jiangsu, Zhejiang, Beijing, Shanghai, and other places, while Qinghai, Ningxia, Xizang, and other provinces have a very low level of S&T innovation, and many years are negative, that is, below the standard value. Therefore, the results of empirical analysis show that there are obvious regional differences in the level of S&T innovation in the four regions. The eastern region has the highest level of S&T innovation, which is higher than the central region and northeast region, and the western region has the lowest comprehensive evaluation value of S&T innovation as shown in Table 3.

3.2. Analysis of Financial Support. The comprehensive evaluation level of S&T innovation of each province in 14 years calculated by factor analysis was taken as the variable, and the financial scale, financial structure, and financial efficiency were taken as the variable to calculate the quantitative relationship between S&T innovation and financial support in four regions. In order to eliminate the possible influence of variable heteroscedasticity and avoid the occurrence of false regression, it is necessary to perform logarithmic processing on panel data first and then conduct a unit root test to determine whether the variable data are stable. Under the operation of Eviews software, a unit root test was carried out on the four regions, respectively. Test results are shown in Table 4. Among the original sequence data, only PP-Choi Z-Stat and Levin, Lin, and Chut tests were significant at 10% and 5% levels in the eastern region. The test results of the other two methods accepted the assumption that the original sequence had unit roots, and the ADF test results should be mainly referred to at this time. Therefore, it can be considered that the original sequences of the four regions have unit roots and belong to nonstationary sequences. In first-order difference series data, except for ADF and Im in northeast China, Pesaran and Shin W-Stat tests are significant at a 10% level, and the other test results are significant at a 1% level. Therefore, first-order difference data in the four regions reject the null hypothesis of the existence of unit roots and consider them as stationary series.

According to the results of the unit root test, each variable is a first-order integration sequence, and the cointegration test can be carried out to verify whether there is a long-term equilibrium relationship between variables through the results of the cointegration test so that the design of the regression equation can be more reasonable. There are many ways to test for cointegration, which include 4 intragroup statistics (panel V statistics, panel RHO statistics, panel PP statistics, and panel ADF statistics) and 3 intergroup statistics (group RHO statistics, group PP statistics, and group ADF statistics). When the number of samples is large, these 7 statistics have good stability and testing efficiency. When the number of samples is less than 20, panel ADF and group ADF statistics become the optimal test methods. Since this study needs to carry out the cointegration test for the four regions and each region contains samples less than 20, only the test results of panel ADF and group ADF statistics are considered. Table 5 shows

Table 5: Cointegration test results.

Area	Inspection methods	Statistics	Probability	Weighted statistics	Probability
Eastern region	Panel ADF statistics	−2.281	0.009	−3.025	0.001
	Group ADF statistics	−2.395	0.006		
Central region	Panel ADF statistics	−4.590	0.000	−2.541	0.004
	Group ADF statistics	−4.611	0.000		
Western region	Panel ADF statistics	0.642	0.723	−2.726	0.002
	Group ADF statistics	−2.644	0.003		
Northeast region	Panel ADF statistics	−2.899	0.001	−2.478	0.005
	Group ADF statistics	−2.767	0.002		

Table 6: Regression results.

Area	Variable	Coefficient	Standard deviation	t statistics	Probability
Financial scale (FSC)	Eastern	0.03204	0.00605	5.12925	0.00000
	Central	0.01967	0.00308	6.19772	0.00000
	Western	0.01510	0.00038	38.11605	0.00000
	Northeast	0.02092	0.00615	3.29635	0.00165
Financial structure (FST)	Eastern	0.04612	0.01019	3.77706	0.00019
	Central	0.03157	0.00387	9.35948	0.00000
	Western	0.01777	0.00061	35.83719	0.00000
	Northeast	0.02914	0.01121	7.98095	0.00000
Efficiency of the financial structure (FEF)	Eastern	0.00493	0.00203	2.35151	0.01609
	Central	0.00109	0.00061	1.74352	0.07364
	Western	0.00089	0.00011	4.98282	0.00000
	Northeast	0.00118	0.05506	1.23784	0.08634
Intercept item	Eastern	0.04343	0.00790	5.32830	0.00000
	Central	0.01377	0.00196	6.80450	0.00000
	Western	0.03523	0.00027	126.68435	0.00000
	Northeast	0.02479	0.00862	2.40021	0.01405

the cointegration test results of the four regions calculated by Eviews software.

The results of the cointegration test showed that panel ADF within the group was significant at a significance level of 1% after weighting, and group ADF between the groups was also significant at a significance level of 1%. Therefore, the test results reject the null hypothesis that there is no cointegration relationship between variables, and we believe that there is a cointegration relationship between variables in the four regions, which is convincing for regression analysis.

3.3. Analysis of Regression Results. According to the results of the unit root test and cointegration test, the data of the four regions in 14 years were analyzed by regression analysis. In order to determine which panel data model to adopt, it is necessary to first determine the form of influence and determine whether it is fixed influence or random influence. The Hausman test is generally used to test the form of influence, but this method often results in counterproductive results. In addition, according to the nature of the data, it can also decide which form of influence to choose. If there is random sampling and the sample reflects the overall nature, the random form of influence is suitable. If the data are aggregate data with small differences and need to be compared with each other, the fixed influence form is suitable. The purpose of this study is to explore the data consistency within the region and to compare the differences between regions, and a fixed-effect model needs to be established. According to the calculation results of Eviews software, the regression model of panel data of the four regions is obtained. The details are listed in Table 6.

As shown in Table 6, the regression coefficients of variables have all passed the significance level test, and the regression equations of the four regions can be further obtained as follows:

Eastern region:

$$\mathrm{STI} = 0.04343 + 0.03204 * \mathrm{FSC} + 0.04612 * \mathrm{FST} + 0.00493 * \mathrm{FEF}. \tag{34}$$

Central region:

$$\mathrm{STI} = 0.01377 + 0.01967 * \mathrm{FSC} + 0.03157 * \mathrm{FST} + 0.00109 * \mathrm{FEF}. \tag{35}$$

Western region:

$$\mathrm{STI} = 0.03523 + 0.01510 * \mathrm{FSC} + 0.01777 * \mathrm{FST} + 0.00089 * \mathrm{FEF}. \tag{36}$$

Northeast region:

$$\mathrm{STI} = 0.02479 + 0.02092 * \mathrm{FSC} + 0.02914 * \mathrm{FST} + 0.00118 * \mathrm{FEF}. \tag{37}$$

It can be seen from the regression results that the coefficient of financial scale is positive, indicating that the expansion of the financial system scale can promote the improvement of technological innovation levels in the four regions. However, the influence degree of financial scale on scientific and technological innovation is different among different regions, and the order from large to small is eastern region > northeast region > central region > western region. The influence coefficient of the eastern region is the largest because the financial system of the eastern coastal provinces is relatively perfect. The rapid development of banks and security markets represented by Beijing, Shanghai, and Guangdong greatly promotes the improvement of regional scientific and technological innovation levels. At the same time, due to the large scale of enterprises and many listed companies, the expansion of the scale of the financial system can quickly transfer to the scientific and technological innovation of enterprises. Due to the remote location of most provinces in western China, the banking industry develops slowly, and the security market as a new financing method is also in its infancy. Local governments and enterprises do not pay enough attention to scientific and technological innovation, which is ultimately manifested in the insufficient support for regional S&T innovation from the expansion of financial scale.

There is a positive correlation between financial efficiency and the technological innovation level, and the improvement of financial efficiency can promote the improvement of the regional technological innovation level. Financial efficiency reflects the capital conversion efficiency of bank intermediary institutions. The greater the efficiency, the faster the banking institutions can convert deposits into loans and invest in enterprises. Relatively speaking, the use of capital efficiency is higher, and the promotion of scientific and technological innovation is greater. In general, the coefficient of financial efficiency is relatively small compared with the other two variables because banking institutions convert deposits into loans and issue them to enterprises, which then partially apply these funds to scientific and technological innovation. After capital transfer and filtering twice, the impact of financial efficiency on scientific and technological innovation is reduced.

4. Conclusion

This study analyzes the relationship between financial support and regional science and technology innovation and productivity in different regions of China through multivariate data statistics. The intrinsic influence mechanism of financial [34] support on S&T innovation and production efficiency is explored, and the current development status of S&T innovation in different regions of China and the current status of direct and indirect financing support for S&T innovation are analyzed, and the constraints of financial support on S&T innovation in China are derived. The results of the empirical analysis show that the financial scale, financial structure and financial efficiency variables are all positively related to the level of S&T innovation, but the influence coefficients are different for the four regions. In terms of the degree of influence of each variable, the financial support for S&T innovation in the eastern region mainly comes from the general capital market, which is mainly stock based, and the openness and maturity of the capital market directly affect the supply of funds to enterprises. Strong financial support can effectively improve the region's S&T innovation, and innovation in S&T can effectively improve production efficiency.

Data Availability

The data supporting the current study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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