Empirical Study on Regional Technological Innovation Capacity Difference in China

Yan Xiaofei Du Xiufang
Economics and Management School, Beijing Institute of Petrochemical Technology, P.R.China, 102617
(Email: yanxiaofei@bipt.edu.cn, duxiufang@bipt.edu.cn)

Abstract China's economy has been growing fast in recent years, but there are great differences of growth rates in different regions. One of the main causes is that the technological innovation capacity is not of the same in different regions. In order to understand more clearly the differences of regional technological innovation capacity, we establish an evaluating indicator system which is accomplished on the basis of previous studies and the principles of all-around perspectives, close relationship and data accessibility, and through careful comparison and selection. Subsequently, we use SPSS software and factor analysis method, and adopt statistics of 2006 to do empirical study on the capacity of scientific study and technology innovation in 30 provinces, municipalities and autonomous regions of China and make relevant analysis on the results.
Key words capacity, empirical study, factor analysis, regions, technological innovation

1 Introduction

Innovation is the main dynamic of regional economic growth and sustainable development. In China, 31 provinces, municipalities and autonomous regions (not including Hong Kong, Macao and Taiwan) are of uneven development, the primary cause is the differences lying in their innovation capacity. In order to balance the regional economic development or prevent the differences from expanding, it is necessary to evaluate scientifically the regional innovation capacity to realize the strength and weakness on innovation of every region.

Numerous efforts are made to study the regional innovation capacity from different aspects. In the aspect of analyzing approaches, comprehensive index [1] [2], analytic hierarchy process [3] [4], grey relation grade analysis [5] and factor analysis [6] [7] are largely adopted. In the aspect of perspective, some researches are intended on evaluation methods, as well as others may practice empirical study. In the aspect of targets scope, there are researches focused on only one region, on several regions, or on a whole nation. In this article, we apply the factor analysis to make empirical study on the technological innovation capacity of 30 regions (not including Tibet), and whole analysis is based on the statistics of 2006.

Similar researches have been carried out, for instance, Wu xianying [8] (2003) selected 14 indicators, analyzed the technological innovation capacity of 30 regions and gave each of them a rank, based on the statistics of 1998-1999; Zheng bohong and Peng jizuo [9] (2003) selected 23 indicators, evaluated and ranked the regional innovation capacity of 29 regions according to the statistics of 2000; Ren shenggang and Peng jianhua [10] (2007) selected 28 indicators, evaluated and ranked the regional innovation capacity of 31 regions based on the statistics of 2003. The data used by them don't have long intervals, but the results turned out to be of great differences. For example, the rank of Guangdong in the above studies is respectively the 15th, 3rd and 2nd, and that of Tianjin is the 14th, 4th and 14th; Zhejiang the 17th, 8th and 5th; Fujian the 25th, 10th and 15th. The main cause of this phenomenon is the different concept about regional innovation, which led to the different evaluation indicators system. Some people insist that the issue should be appraised in the aspect of technological innovation capacity, while others regard it as a systematic project (including technological innovation, organizational innovation, system innovation and management innovation), in which government, enterprises and technology institute are involved.

We insist that the regional innovation capacity mainly refers to the technological innovation capacity which is supposed to be measured by regional scientific study and technology innovation capacity. We evaluate the regional technological innovation capacity from both mentioned aspects, because scientific study sets the base for technology innovation, which in turn promises the effective utilization of the former. So when we establish the assessing indicator system, the emphasis is placed on the evaluation of creativity and originality of scientific study and technology innovation.

2 Methods and Data
2.1 Model
Factor analysis plays a major role in multivariate statistical analysis, which concentrates on the interrelationship of multi-variables. In its process, the variables with complicated connections are integrated into several hypothetical variables (factors) which have fixed linear relationship with the response variables. The basic theory is: through the research on the internal structure of variable correlation coefficients matrix, we can extract several comprehensive variables that can account for as much of the correlation between the response variables as possible. Therefore, factor analysis is a process that explores how to condense the over-abundant response variables into common factors with the minimum missing information, just to simplify the analysis [11].

Table 1 Regional Technological Innovation Indicator System

The first-level indicators	The second-level indicators	Variables
Supporting condition	Regional GDP (100 million Yuan)	X_1
	Number of R&D institutions of higher education (unit)	X_2
	Personnel with college and higher level education (person)	X_3
	Total S&T personnel (person)	X_4
Actual input	Total funding for S&T activities（10 000 Yuan）	X_5
	Total R&D expenditures (100 million Yuan)	X_6
	Local government appropriating funds for S&T（100 million Yuan）	X_7
	Full-time equivalent of R&D personnel total (man-year)	X_8
The results of R&D	Number of invention patents Granted by country (Piece)	X_9
	Number of papers taken by major foreign referencing system (piece)	X_{10}
Technology exchange	Value of concluded contracts of technology transfer (10 000 Yuan)	X_{11}
	Value of Contracts purchasing Foreign Technologies（USD 10 000）	X_{12}

The mathematical model of the factor analysis is

$$X = AF + \varepsilon \tag{1}$$

Where X=（$x_1,x_2,\ldots,x_p$）^{T} denotes a measureable p-dimension vector；F=（$F_1,F_2,\ldots F_m$）^{T} denotes factor vector, certainly we want m<p；A=（a_{ij}）$_{p\times m}$ denotes factor loading matrix, thereof, a_{ij} is called factor loading which measures the contribution of the j^{th} common factor to i^{th} response variable；ε denotes special factor vector, i.e. a part of the variables, while this part can not be interpreted by common factors.

2.2 Indicator System
Referring to the outcome of previous studies in recent years, we establish an evaluation indicator system on the principles of all-around perspectives, close relationship and data accessibility. It’s a two levels indicator system consisting of 4 first-level indicators: supporting condition, actual input, the results of R&D and technology exchange, and each first-level indicator contains 2-4 second-level indictors [12] [13].

●Supporting condition

Economic strength, R&D institutes and technological talents are the necessary condition of scientific study and technology innovation, so we set this indicator, which comprises 4 second-level indicators: regional GDP, number of R&D institutions of higher education，personnel with college and higher level education and total S&T personnel.

●Actual input

As the input of fund and technological manpower is a guarantee of scientific study and technology innovation, it is necessary to set this indicator, which comprises 4 second-level indicators: total funding for S&T activities, total R&D expenditures, local government appropriating funds for S&T and full-time equivalent of R&D personnel total.

●The results of R&D

The capacity of scientific study and technological innovation in a region can be truly embodied by the R &D results which can really show the originality and creativity, so we set this indicator, which consists of 2 second-level indicators: number of invention patents granted by country and number of papers taken by major foreign referencing system.

●Technology exchange

It is well known that the more activities of technology exchanges in a region, the stronger it's dynamic of innovation. In view of this, we set this indicator, which includes 2 second-level indicators: value of concluded contracts of technology transfer and value of contracts purchasing foreign technologies.

To be convenient, we name the 12 second-level indicators as X_i （i=1,2,3,…,12） (Tab.1). As 30 regions are revolved in this paper, each variable has 30 observations.

2.3 Data

The statistics in this article are derived from China Statistical Yearbook (2007), Statistical bulletin of national financial inputs on science and technology (2006) and Annual Statistical data on science and technology (2006), which are all published by the National Bureau of Statistics.

3 Analyzing Process and Results

3.1 KMO and Bartlett's Test

According the factor analysis theory, we use SPSS16.0 to analyze the original data of the 12 indicators. Before doing that, we should do KMO and Bartlett's test on the data, in order to verify whether or not the data are suitable for factor analysis.

We get the results：The statistic of KMO is 0.821 >0.5; the statistic of Bartlett's Test is 787.485, being big enough, and its corresponding P value is 0.000 <0.05 (Tab.2). These suggest the application of factor analysis is reasonable.

Table 2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.821
Bartlett's Test of Sphericity	Approx. Chi-Square	787.485
	Df	66
	Sig.	0.000

3.2 Standardization

After KMO and Bartlett's test, we also need to standardize the observations of variables. By means of that, the impact of the dimension of the observation and the difference of magnitude can be eliminated; otherwise the analyzing outcome would be influenced.

The formula of standardization is

$$z_{ij} = \frac{x_{ij} - \overline{x}_i}{\sqrt{s_{ii}}} \quad \text{（j=1,2…,n；i=1,2…,p）} \tag{2}$$

Where z_{ij} denotes the standardized value of the j^{th} observation of the i^{th} variable; x_{ij} is the j^{th} observation of i^{th} variable; $\overline{x}_i$ denotes the average of i^{th} variable's observations; s_{ii} denotes the Standard deviation of i^{th} variable's observations.

On account of the standardization, the average of standardized data is 0, with the positive value indicating data above average and the negative as below average.

3.3 Empirical Analysis

By means of SPSS, we practice factor loading estimation on the correlation coefficient matrix of the 12 variables' observations and work out its eigenvalue and the proportion of the total variance. Then principal components can be extracted on the principle that the eigenvalues are greater than 1. The eigenvalues of the first and second components are 9.334 and 1.490, and they can interpret respectively 77.779% and 12.417% of 12 variables' total variance (Table.3).

Table 3 Total Variance Explained by Each Factor

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.334	77.779	77.779	9.334	77.779	77.779
2	1.490	12.417	90.196	1.490	12.417	90.196
3	0.649	5.408	95.604			
4	0.257	2.139	97.743			
5	0.104	0.870	98.613			
6	0.076	0.632	99.245			
7	0.052	0.431	99.676			
8	0.015	0.128	99.804			
9	0.011	0.091	99.895			
10	0.007	0.055	99.949			
11	0.005	0.038	99.988			
12	0.001	0.012	100.000			

In other words, the 2 components account for 90.196% of the information revealed in the response variables. Through factor analysis, the 12 variables are transformed into 2 comprehensive variables.

In order to enable the components to mean explicitly, we need to conduct an orthogonal rotation on the component loading matrix. Then the loading of each response variable on components will differentiate towards the direction of 0 or 1, which makes the component structure much simpler. Thus, we can clarify the real meaning of every component.

Table 4 Rotation Sums of Squared Loadings

Component	Total	% of Variance	Cumulative %
1	5.873	48.941	48.941
2	4.951	41.255	90.196

The method we adopt is Varimax with Kaiser Normalization. After a rotation converged in three iterations, we get the eigenvalues and the proportion of the total variance of the rotated components (Table. 4), as well as the component loading matrix (Table.5). The proportion of the total variance can act as weights of weighted average when the comprehensive scores of the components are calculated.

Table 5 Rotated Component Matrix

variables	Component	
	F_1	F_2
X_1	0.974	0.018
X_2	0.685	0.561
X_3	0.906	0.282
X_4	0.893	0.421
X_5	0.746	0.637
X_6	0.755	0.638
X_7	0.710	0.535
X_8	0.837	0.517
X_9	0.555	0.816
X_{10}	0.338	0.906
X_{11}	0.147	0.955
X_{12}	0.246	0.784

The rotated component matrix reflects the loadings of 12 variables in the 2 components. From that we may notice: The first component (F_1) with high loading from X_1, X_3, X_4 and X_8 reflects regional fund and human resource supporting strength on technological innovation, and the second component (F_2) with high loading from X_{11}, X_{10} and X_9 reflects the capability of science study, technology invention and application.

Table 6 Component Score Coefficient Matrix

Standardized variable	Component	
	FC_1	FC_2
Z_1	0.342	-0.265
Z_2	0.087	0.045
Z_3	0.244	-0.135
Z_4	0.200	-0.072
Z_5	0.087	0.060
Z_6	0.090	0.058
Z_7	0.103	0.027
Z_8	0.153	-0.016
Z_9	-0.031	0.189
Z_{10}	-0.133	0.288
Z_{11}	-0.215	0.362
Z_{12}	-0.132	0.262

As the value of the F_1 and F_2 can not be observed directly, we manage to describe their variation feature and score difference by means of raw data. On account of the relationship between components and variables, we can adopt regression to estimate component score coefficient matrix (Table.6)

Moreover, the covariance of components scores is -2.157×10^{-16} (extremely close to 0) , which means that the scores of 2 components are completely irrelevant.

We put z_{ij} in (3) and reckon the scores of F_1 (FS_1) and scores of F_2 (FS_2) in each region (Table.7).

$$FS = FC^T \times Z \tag{3}$$

Where $FS = (FS_1, FS_2)^T$ is the score vector of component in each region; $Z = (Z_1 \quad Z_2 \quad .... \quad Z_{12})^T$ is the standardized variable vector; FC^T is the transpose of common factor score coefficient matrix.

On the basis of (3), we regard the proportion of the total variance as weights to calculate weighted average, and then we obtain the comprehensive scores (S) of the regional technological innovation capacity. The formula is

$$S = 0.5426 \times FS_1 + 0.4574 \times FS_2 \tag{4}$$

After calculating, we can achieve the S of 30 regions (Table.7). According their scores, we can rank them.

3.4 Result Analysis

From the analyzed outcome, we arrive at the following conclusions:

●According to the order of the comprehensive scores of the common factors, the technological innovation capacity of Beijing, Guangdong, Shanghai and Jiangsu rank 1st, 2nd, 3rd and 4th, yet without evident difference. In fact, they are all located in the prosperous regions. However, the latter ones in the sequence are Qinghai, Hainan, Ningxia, Guizhou, Xinjiang, Gansu and Inner Mongolia, which are all in the western or northwest regions except Hainan.

●According to FS_1 and FS_2, we can see some regions such as Beijing, Shanghai, Tianjin and Chongqing do parade the uppermost capacity of scientific study and technological innovation, even though their technological supporting condition is not much better compared with other regions. This can be explained by the highly efficient application of the technological input in these regions, as well as the remarkable capacity to invent and apply technology. The four regions are all metropolises, which suggest that big cities can exert their technological integration advantage to the fullest.

Table 7 Factor Scores and Comprehensive Scores

Region	FS_1	$Rank_1$	FS_2	$Rank_2$	S	Rank
Beijing	0.14798	10	4.19978	1	1.772279	1
Tianjin	-0.50375	21	0.35563	3	-0.15899	14
Hebei	0.24915	9	-0.63450	28	-0.1426	13
Shanxi	-0.26899	17	-0.40526	24	-0.34233	19
Neimenggu	-0.64924	22	-0.43737	26	-0.55598	24
Liaoning	0.63925	6	0.04369	5	0.353049	7
Jilin	-0.47061	19	-0.07117	9	-0.30932	18
Heilongjiang	-0.18663	15	-0.20597	13	-0.20994	16
Shanghai	-0.15540	14	2.82694	2	1.129194	4
Jiangsu	2.37264	2	0.08045	4	1.387365	3
Zhejiang	1.46470	4	-0.15999	12	0.873427	5
Anhui	-0.19903	16	-0.29487	19	-0.24473	17
Fujian	-0.14490	13	-0.31097	22	-0.19232	15
Jiangxi	-0.44633	18	-0.42060	25	-0.43583	21
Shandong	2.04892	3	-0.72838	29	0.855266	6
Henan	.64655	5	-0.79613	30	0.011395	10
Hubei	0.38613	8	-0.04273	7	0.167443	9
Hunan	-0.00390	11	-0.28063	18	-0.12839	12
Guangdong	2.60165	1	-0.12705	11	1.543188	2
Guangxi	-0.47098	20	-0.46846	27	-0.47355	22
Hainan	-1.17548	29	-0.23726	16	-0.76002	29
Chongqing	-0.65433	23	-0.06671	8	-0.3776	20
Sichuan	0.53001	7	-0.27749	17	0.174386	8
Guizhou	-0.90406	26	-0.29542	20	-0.63764	27
Yunnan	-0.67996	24	-0.29910	21	-0.52472	23
Shaanxi	-0.07960	12	-0.03995	6	-0.08755	11
Gansu	-0.92546	27	-0.09944	10	-0.56212	25
Qinghai	-1.21078	30	-0.20774	14	-0.76683	30
Ningxia	-1.17088	28	-0.21490	15	-0.749	28
Xinjiang	-0.78669	25	-0.38439	23	-0.60755	26

In addition, the some regions such as Gansu, Qinghai, Ningxia and Hainan feature insufficient technological input, which directly impacts their ranks of comprehensive scores, but the scores of F_2 show that their capacities to invent and apply technology are of powerfulness.

Contrasting with them, some regions such as Shandong, Hebei, Henan, Shanxi, Guangdong, Sichuan, Zhejiang, Jiangxi and Fujian, have advantageous economic strength and sufficient resources, yet limited capacity to invent and apply technology. What they are required is to be aware of the role of innovation in economic development, and seek out institutional or managing shortages, then, construct an effective innovation-encouraging mechanism to largely inspire innovation activity. If so, they will take the advantage of their sufficient technological input and enhance the efficiency of technological invention and application.

From FS_1 and FS_2, we can see some regions such as Liaoning, Heilongjiang, Jiangsu and Hubei have sufficient technological input and accordingly show stronger capacity of scientific study and technology invention and application. Generally speaking, they have competitiveness on technological innovation. On the contrary, some regions such as Xinjiang, Inner Mongolia, Guangxi, Guizhou and Yunnan are limited in both respects. Among them, Xinjiang, Guizhou and Yunnan's input are not serious insufficient, but very week performance on technology invention and application, while the cases of Inner Mongolia and Guangxi are just the opposite.

4 Conclusions

The statistics adopted by this article are all released by the National Bureau of Statistics, with high authority, comparability and accessibility. On account of this, taking the measure of factor analysis in this empirical study is convincing. The study pays considerable attention to the technological innovation capacity in 30 regions of China, which differ greatly among each other as what is shown in the study outcome. It also suggests that the crucial points in technological innovation capacity are actual input, reasonable resources distribution and the application of R&D results, which may lead to the decline of technological innovation capacity if ignored. Besides, it can be noticed in the analysis that the technological innovation capacity in some regions is impacted by its weak capacity of R&D results application, even though they have enough fund and human resource input.

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