

Research on Evaluation of China's Data Factor Input Level Based on Global Principal Component Analysis: An Analysis of Provincial Panel Data

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Received: 21 October 2023; Accepted: 12 November 2023; Published: 24 December 2023

Abstract:

This paper aims to analyze the panel data of various provinces in China to study the measurement of data factor input levels and their spatio-temporal patterns. The paper highlights the importance of data factors as the core engine of digital economic development and discusses the challenges faced by China's economic growth model. A set of 14 relevant indicators, including basic input, development input, investment input, and integration input, is selected to construct an index system for measuring data factor input levels. By using the method of global principal component analysis, a comprehensive quantitative evaluation of data factor input levels for 30 provincial administrative regions from 2012 to 2021 is conducted, and their spatio-temporal differences are analyzed. Finally, through a comparative analysis of the evolution trends of data factor input in China, relevant suggestions are proposed to provide scientific support for China's sustainable development.

Keywords:

Data Factor Input, Global Principal Component Analysis, Comprehensive Evaluation

1. Introduction

In 2021, the State Council of China explicitly stated in the "14th Five-Year Plan for the Development of the Digital Economy" that data factors are the core engine for deepening the development of the digital economy. The role of data in improving production efficiency has become increasingly prominent, making it one of the most characteristic production factors of the times. In April 2020, the State Council issued an important document, namely the "Opinions of the CPC Central Committee and the State Council on Constructing a More Perfect System and Mechanism for Market-Based Allocation of Factors," which officially included data as a production factor. The promulgation of this policy categorizes data as a production factor on par with traditional factors such as land, labor, capital, and technology for the first time in

China. It also recognizes the economic growth prospects associated with data as a production factor.

China is one of the most populous countries in the world, and its economic development has always been at the forefront globally. However, China's economic growth model also faces a series of challenges. In order to promote sustainable economic growth, the government needs to continuously increase investments in various fields, especially in data factors. Data is one of the important production factors in modern economy, and it plays a significant role in promoting economic development, improving industrial competitiveness, and creating employment opportunities. Therefore, measuring the level of data factor input in various provinces of China is crucial for formulating scientific economic policies and achieving sustainable economic development. [1]

This paper aims to explore the data factor input levels and spatio-temporal differences among different provinces in China by analyzing panel data of Chinese provinces. Specifically, the paper will analyze the following aspects: Firstly, it introduces the background and current situation of data factor input in China through a literature review. Secondly, it constructs an index system to measure the level of data factor input, including basic input, development input, investment input, and integration input. Then, it measures the data factor input levels of each province based on provincial panel data and analyzes the spatio-temporal differences in data factor input levels among different provinces. Finally, through a comparative analysis of temporal and spatial patterns, it attempts to explain the evolving trends of data factor input in China and provides relevant suggestions to support China's sustainable development scientifically. [2]

2. Literature Review

On the one hand, some scholars have devoted themselves to studying the impact of data factor allocation on productivity improvement and attempted to construct different indicator systems and calculation methods. Among them, Li Zhiguo (2021) constructed a multidimensional indicator system for the development of the digital economy and the level of data factor allocation. Yang Yan (2021) constructed an indicator system for data factor flow environment based on the perspective of factor flow and used the entropy method for calculation. Yan Meng et al. (2021) constructed an index for the market-oriented development of data factors based on dimensions such as market foundation, market size, and market environment, but their calculation method had a problem of subjective weighting. Previous studies often used methods such as principal component analysis and entropy method, but these methods have limitations. Projection pursuit technique is a more robust and effective comprehensive evaluation method that can handle high-dimensional data. It was initially used to measure comprehensive indicators such as resources and environment and has gradually been applied to economic research in recent years. For example, Li Lin (2019) used the projection pursuit model to dynamically evaluate the index system for the quality evaluation of Hunan's economic development. Introducing genetic algorithm into the projection pursuit model can optimize the solution speed, making it more widely used in the field of data calculation indicator values (Luo Jianwen et al., 2020). These studies contribute to understanding the role of data factors in economic growth and guiding policy and industrial development. [3]

On the other hand, in the research on data factor empowerment, scholars have proposed different definitions. Liu Jing et al. (2020) argue that data empowerment mainly refers to the enhancement of traditional business performance by enterprises using digital technology in the aspects of data assets and the economy. Zhang Zhengang et al. (2021) define it as the process in which enterprises collect, organize, and analyze customer data using emerging technologies such as big data to build large databases that support business decision-making. Li Tianyu and Wang Xiaojuan (2021) suggest that the digital economy relies on data and digital technology to optimize resource allocation, reduce costs, and drive innovation, representing a new technological-economic paradigm. Regarding the empowerment of other production factors by data factors, Guan Hui (2022) points out that data, as a new type of production factor, has unique value in agricultural empowerment, promoting better aggregation of “human” factors, broader industrial symbiosis, and more refined agricultural governance and services. Zhong Zhen (2021) states that data is a crucial production factor in the era of informatization, empowering traditional agricultural production factors, and serving as the fundamental resource for the digital transformation of agriculture and the acceleration of agricultural modernization. Lv Tie (2022) focuses on the enterprise level and discusses the intrinsic logic of digital transformation in manufacturing companies based on the perspective of data factor empowerment of traditional factors. These studies contribute to a deeper understanding of data factor empowerment and the development of the digital economy, offering insights and guidance for achieving digital transformation. [4]

Through the literature review, it is found that research on data factors focuses on their role in economic growth and the direction of data factor empowerment. Regarding the impact of data factor allocation on productivity improvement, scholars have proposed different indicator systems and calculation methods. In terms of data factor empowerment, scholars have put forward different definitions and perspectives. These studies contribute to a better understanding of the role of data factors in economic growth and the digital transformation of businesses, guiding policy-making and industrial development, and promoting the development of the digital economy. Specifically, the existing research exhibits the following characteristics: (1) Although the connotation of the digital economy is continuously enriched, the development of data factors in China needs further clarification and clarification; (2) Existing developments in the digital economy are mostly abstract and general guiding goals, lacking strategies and measures that involve specific regions and industries; (3) The constraints on the development of the digital economy are relatively complex, requiring a clear understanding of the constraining factors at different levels; (4) Existing evaluation indicator systems for digital economy development are mostly relatively macro-level, lacking statistics and empirical testing of data factor indicators. In particular, the input and output indicators for data factors are relatively vague. Therefore, for the evaluation of data factor input in China, there is an urgent need to establish a comprehensive and diversified indicator system that meets the requirements of the new era, further explore high-quality development strategies and paths for the digital economy, and conduct research considering the actual conditions of different spatial and temporal patterns.[5]

3. Research Design

3.1. Indicator System

This study measures the level of data factor input in China from the perspective of data factor input. In the context of rapid development of the digital economy, referring to relevant studies by scholars such as Ma Luyin (2023), Yang Yan (2021), Wan Xiaoyu (2022), and Yang Feihu (2022), an indicator system for data factor input is constructed from four aspects: data factor infrastructure input, data factor development input, data factor utilization input, and data factor integration input (see Table 1). Based on the current development status of China's digital economy, relevant data on data factor input in China from 2012 to 2021 were collected and organized. An empirical evaluation of the level of data factor input in China was conducted, forming an indicator assessment and longitudinal analysis of data factor input in China. Furthermore, a comparative analysis of the level of data factor input from 2012 to 2021 was conducted in terms of temporal and spatial patterns to compare the characteristics and trends of data factor input in China. Some of the indicator data can be directly obtained from yearbooks, while others can be processed using relevant theories and calculation formulas to determine indicator weights. [6]

Table 1. Indicator System for Data Factor Input Level.

Goal Level	Criteria Level	Indicator Level	Unit
Data Factor Input Indicator System	Data Factor Infrastructure Input	Total Length of Optical Fiber Cables	Kilometers
		Mobile Telephone Exchange Capacity	Ten Thousand Households
		Number of Internet Broadband Access Ports	Ten Thousand Units
		Number of Domain Names	Ten Thousand Units
	Mobile Telephone Exchange Capacity	R&D Expenditure Intensity	Billion Yuan
		R&D Personnel Full-time Equivalent	Person-years
		Number of Patent Applications	Pieces
	Number of Internet Broadband Access Ports	Express Service Revenue	Ten Thousand Yuan
		Software Business Revenue	Ten Thousand Yuan
		Total Telecommunications Revenue	Billion Yuan
		E-commerce Sales Volume	Billion Yuan
	Number of Domain Names	Proportion of E-commerce Transactions by Enterprises	%
		Proportion of E-commerce Sales Volume	%
		Digital Inclusive Finance Index	%

3.2. Model Selection

Evaluating the level of data factor input involves multiple indicators and belongs to a multi-attribute decision-making problem. Therefore, a comprehensive evaluation method is needed to calculate the results. To make the data comparison more objective, intuitive, and in line with the actual situation, this study adopts the principal component analysis (PCA) method to extract the most important features from high-dimensional data, thereby reducing data dimensionality, simplifying data analysis, and

facilitating a better understanding of the data and the discovery of patterns and underlying structures. The weights and composite scores are calculated and processed using Stata software. To eliminate the dimensional differences between different indicators, all original data are standardized. Then, a KMO test and Bartlett's sphericity test are conducted. Based on the eigenvalues and cumulative variance contribution rate, the principal components are extracted. Typically, if the first n principal components can reflect 85% of the information from the original indicators, the extracted n principal components are considered acceptable. Finally, a factor loading matrix is established to explain the main information reflected by each principal component. Based on the principal component score coefficient matrix, linear models of each principal component are obtained. The variance contribution rate of each principal component is used as weights to calculate the weighted sum of the n principal components, resulting in a comprehensive evaluation model for evaluating the data factor input of each province. The comprehensive scores of data factor input levels for each province are then calculated, and the provinces are ranked based on the comprehensive scores. [7]

3.3. Data Sources

The data for this study mainly come from the National Bureau of Statistics, China Statistical Yearbook, China Science and Technology Statistical Yearbook, China High-Tech Industry Statistical Yearbook, and the EPS database of the China Economic and Social Big Data Research Platform. The panel data cover 30 provincial-level regions in China from 2012 to 2021, excluding Tibet, Hong Kong, Macau, and Taiwan. For missing data in certain years, linear interpolation is used to fill the gaps. The above text and table have been translated into English.

4. Empirical Analysis

4.1. Feasibility Test

Stata 16 is used to analyze the raw data. First, the data is standardized. Then, the feasibility of the data is tested using the KMO (Kaiser-Meyer-Olkin) test and Bartlett's test. To eliminate the influence of different units among variables, the data is standardized. The feasibility of the data is tested using the KMO test. The KMO test is an important indicator for measuring the strength of the correlation between variables. It is mainly obtained by comparing the correlation coefficients and partial correlation coefficients of two variables. The KMO value ranges from 0 to 1, and a higher KMO value indicates stronger commonality among variables, making it more suitable for principal component analysis.

From Table 2, it can be seen that the KMO value is 0.856, which is greater than 0.5. The Bartlett's test statistic value is 5470.953, and the obtained p-value is 0.000, which is less than the significance level of 5%. This indicates that the data is suitable for principal component analysis.

Table 2. KMO and Bartlett's Test Results.

KMO test		0.856
Bartlett's test for sphericity	Chi-square	5470.953
	df	91
	Sig.	0.000

4.2. Determination of Principal Components

Using Stata 16, a PCA (Principal Component Analysis) analysis is conducted on the data, resulting in the eigenvalues and factor contribution rates shown in Table 3. Following the criteria of cumulative contribution rate exceeding 80% and eigenvalues greater than 1, three major factors can be extracted from the initial 14 indicators. The cumulative variance contribution rate of these three major factors reaches 82.37%, indicating that very little information is discarded, and these three principal components essentially encompass all the information possessed by the indicators. Therefore, the results of the factor analysis are considered reliable. Additionally, the scree plot also indicates the selection of the first three principal components.

Table 3. Eigenvalues and Factor Contribution Rates.

Component	Eigenvalue	Variance Contribution Rate	Cumulative Variance Contribution Rate
1	7.98	0.5701	0.5701
2	2.33	0.1665	0.7366
3	1.21	0.0871	0.8237
4	0.57	0.0413	0.8650
5	0.49	0.0357	0.9007
6	0.40	0.0287	0.9294
7	0.31	0.0222	0.9516
8	0.24	0.0177	0.9693
9	0.14	0.0100	0.9793
10	0.10	0.0073	0.9866
11	0.08	0.0060	0.9926
12	0.05	0.0038	0.9964
13	0.02	0.0020	0.9984
14	0.02	0.0016	1.0000

4.3. Determination of the Meaning of Principal Components

In order to further extract the information contained in the common factors and make the meaning of the common factors more apparent, a varimax orthogonal rotation is applied to maximize the differences in variances among the factors, facilitating a better interpretation of the extracted factors. Through factor rotation, the rotated component matrix shown in Table 4 is obtained. From Table 4, it can be observed that the following 9 indicators: total length of optical cable routes, mobile telephone exchange capacity, number of internet broadband access ports, number of domain names, R&D personnel full-time equivalent, number of patent applications, revenue from express delivery services, revenue from software services, and e-commerce sales, load heavily on the first common factor. Therefore, the first common factor can be defined as the “Data Infrastructure and R&D Factor.” R&D expenditure intensity, the proportion of e-commerce transaction-active enterprises, and the proportion of e-commerce sales load heavily on the second factor. Hence, the second factor can be defined as the “Data Innovation Factor”. The third principal component exhibits significant explanatory power for the Digital Inclusive Financial Index and the proportion of e-commerce transaction-active enterprises, suggesting that it can be defined as the “Data Integration Factor”

Table 4. Rotated Component Matrix.

Variable	Factor 1	Factor 2	Factor 3
mmx_x1	0.7222	-0.5438	0.2919
mmx_x2	0.7646	-0.4769	-0.1058
mmx_x3	0.8593	-0.4231	0.1027
mmx_x4	0.7325	0.1874	-0.0136
mmx_x5	0.5993	0.6058	-0.1961
mmx_x6	0.8288	-0.3314	-0.3110
mmx_x7	0.9130	-0.1909	-0.2254
mmx_x8	0.8408	0.0329	-0.1854
mmx_x9	0.8853	0.2425	-0.2180
mmx_x10	0.6766	-0.3163	0.2302
mmx_x11	0.8882	0.3283	-0.1668
mmx_x12	0.5633	0.4126	0.5530
mmx_x13	0.5331	0.7856	-0.0284
mmx_x14	0.6177	0.1592	0.6764

4.4. Calculation of Scores and Rankings

Using Stata 16 software, the scores for the three principal components are computed for each province. However, using the score of a single principal component alone only reflects a specific aspect of economic development and cannot provide a comprehensive evaluation of the economic dynamics of each province. Therefore, in this study, the variance contribution rates of the three principal components are used as weights. Each weight is multiplied by the corresponding score of the principal component, and the results are summed to obtain the score function S for the comprehensive economic development level. The specific expression of the score function is as follows: $S = (0.5701 * f1 + 0.1665 * f2 + 0.0871 * f3) / 0.8237$.

Based on this model, the scores for the comprehensive economic development level and rankings of 30 provinces in China from 2012 to 2021 are calculated (refer to Table 5).

Table 5. Comprehensive Scores and Rankings of Data Input Levels for Each Province.

Province	2012		2013		2014		2015		2016	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Beijing	0.16	2	0.47	2	0.80	1	1.23	1	1.44	1
Tianjin	-0.43	6	-0.35	7	-0.15	7	0.13	7	0.12	9
Hebei	-0.81	16	-0.67	17	-0.54	19	-0.37	20	-0.20	17
Shanxi	-0.93	23	-0.82	23	-0.70	23	-0.53	27	-0.43	25
Inner Mongolia	-0.97	27	-0.86	26	-0.75	28	-0.53	25	-0.41	24
Liaoning	-0.68	9	-0.54	9	-0.43	12	-0.22	13	-0.23	18
Jilin	-0.92	21	-0.86	27	-0.75	27	-0.61	30	-0.55	29
Heilongjiang	-0.95	26	-0.78	21	-0.70	25	-0.55	28	-0.52	28
Shanghai	0.04	4	-0.03	5	0.57	3	0.86	3	1.04	3
Jiangsu	-0.14	5	0.16	3	0.33	4	0.55	5	0.64	5
Zhejiang	0.10	3	0.12	4	0.26	5	0.58	4	0.82	4
Anhui	-0.72	11	-0.57	11	-0.32	9	-0.09	10	0.02	10

Fujian	-0.57	8	-0.44	8	-0.29	8	-0.03	8	0.26	7
Jiangxi	-0.86	19	-0.77	20	-0.63	21	-0.33	19	-0.34	22
Shandong	-0.43	7	-0.05	6	0.02	6	0.17	6	0.46	6
Henan	-0.79	15	-0.65	14	-0.48	15	-0.27	15	-0.12	13
Hubei	-0.73	12	-0.57	12	-0.41	11	-0.15	11	-0.02	11
Hunan	-0.76	14	-0.63	13	-0.48	14	-0.31	18	-0.13	15
Guangdong	0.24	1	0.48	1	0.71	2	1.07	2	1.36	2
Guangxi	-0.90	20	-0.77	19	-0.62	20	-0.46	22	-0.31	21
Hainan	-0.94	25	-0.80	22	-0.50	16	-0.22	12	-0.15	16
Chongqing	-0.74	13	-0.66	15	-0.43	13	-0.23	14	-0.05	12
Sichuan	-0.69	10	-0.54	10	-0.33	10	-0.05	9	0.17	8
Guizhou	-0.93	22	-0.83	24	-0.69	22	-0.48	23	-0.29	20
Yunnan	-0.83	18	-0.77	18	-0.54	18	-0.30	17	-0.26	19
Shaanxi	-0.81	17	-0.67	16	-0.51	17	-0.30	16	-0.12	14
Gansu	-0.94	24	-0.84	25	-0.71	26	-0.53	24	-0.43	26
Qinghai	-1.06	30	-0.96	30	-0.85	30	-0.38	21	-0.40	23
Ningxia	-0.98	28	-0.86	28	-0.70	24	-0.53	26	-0.46	27
Xinjiang	-1.01	29	-0.90	29	-0.76	29	-0.59	29	-0.60	30
Province	2017		2018		2019		2020		2021	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Beijing	1.78	1	1.90	2	2.34	2	2.55	2	2.89	1
Tianjin	-0.02	12	0.09	14	0.15	16	0.29	16	0.42	12
Hebei	-0.13	16	0.00	16	0.16	15	0.33	14	0.22	16
Shanxi	-0.41	24	-0.18	22	-0.16	23	-0.07	23	-0.10	23
Inner Mongolia	-0.39	23	-0.36	24	-0.24	24	-0.14	24	-0.12	24
Liaoning	-0.17	17	-0.04	17	0.09	18	0.17	18	0.11	18
Jilin	-0.51	28	-0.43	28	-0.35	27	-0.31	27	-0.32	29
Heilongjiang	-0.46	26	-0.42	27	-0.35	26	-0.26	26	-0.27	27
Shanghai	1.05	3	1.18	3	1.46	3	1.71	3	1.89	3
Jiangsu	0.78	5	1.07	4	1.35	4	1.61	4	1.55	4
Zhejiang	0.85	4	1.06	5	1.34	5	1.53	5	1.44	5
Anhui	0.10	9	0.30	9	0.54	9	0.63	8	0.60	9
Fujian	0.54	7	0.61	7	0.72	7	0.62	9	0.68	8
Jiangxi	-0.18	18	-0.05	18	0.12	17	0.24	17	0.19	17
Shandong	0.63	6	0.99	6	0.99	6	1.15	6	1.22	6
Henan	-0.03	13	0.18	10	0.32	11	0.44	12	0.26	15
Hubei	0.06	10	0.17	11	0.37	10	0.50	10	0.44	11
Hunan	-0.06	14	0.11	13	0.29	13	0.42	13	0.34	13
Guangdong	1.59	2	2.09	1	2.56	1	2.84	1	2.65	2

Guangxi	-0.28	22	-0.18	21	0.01	20	0.14	20	0.08	19
Hainan	-0.19	19	-0.17	20	-0.09	22	-0.02	22	-0.03	22
Chongqing	0.02	11	0.16	12	0.31	12	0.48	11	0.48	10
Sichuan	0.28	8	0.44	8	0.67	8	0.87	7	0.76	7
Guizhou	-0.28	21	-0.19	23	-0.09	21	0.02	21	0.02	20
Yunnan	-0.24	20	-0.13	19	0.03	19	0.15	19	0.01	21
Shaanxi	-0.07	15	0.06	15	0.22	14	0.32	15	0.28	14
Gansu	-0.47	27	-0.37	25	-0.28	25	-0.21	25	-0.21	25
Qinghai	-0.52	29	-0.48	30	-0.42	30	-0.36	30	-0.26	26
Ningxia	-0.45	25	-0.41	26	-0.36	28	-0.32	28	-0.28	28
Xinjiang	-0.56	30	-0.46	29	-0.40	29	-0.32	29	-0.34	30

4.5. Empirical Results Analysis

It can be seen that Beijing, Guangzhou, and Shanghai consistently rank among the top three in terms of comprehensive scores, significantly higher than other provinces. These regions have higher levels of data input and stable development. Provinces and cities with higher scores are mainly concentrated in the eastern coastal areas, such as Jiangsu, Zhejiang, and Fujian. The superior geographic locations of these eastern coastal cities contribute to their higher scores. Shaanxi, Hunan, Hebei, and Tianjin rank in the middle in terms of comprehensive scores, indicating moderate levels of data input and significant room for improvement. Xinjiang, Qinghai, Ningxia, Jilin, and Gansu rank lower in terms of comprehensive scores, indicating lower levels of data input that need to be improved.

From a regional perspective, there is a lack of homogeneity in data input within provinces, indicating significant spatial disparities. Beijing, Shanghai, and Guangzhou, as regional central cities, have outstanding comprehensive scores in data input. They have abundant public social service resources such as education and healthcare, favorable policies, good economic development, and ample employment opportunities. The strong attractiveness of these cities drives urbanization and digitalization. Eastern coastal cities benefit from their advantageous geographical locations, convenient transportation, and rich resources, which contribute to relatively good scores in data input. On the other hand, western provinces such as Guizhou, Yunnan, and Gansu are influenced by factors such as geographical location and technological level, resulting in slow data input and relatively lower scores, ranking towards the bottom. Overall, the economic development level decreases sequentially from east to central to west.

From a time series perspective, the data input levels of various provinces have been increasing over time, indicating comprehensive and favorable development of the digital economy. The national level of data input has been continuously increasing, and the regions with concentrated data input levels have been shifting to the right. The number of provinces with rising comprehensive scores has increased, and the gap in data input levels among provinces has been gradually widening.

5. Conclusions

Based on the quantitative analysis of data input levels, there are significant differences in data input levels among provinces in China. Some regions demonstrate higher levels of data input, while others have relatively lower levels. Furthermore,

over time, the data input levels have been increasing nationwide, but the disparities among provinces have been growing.

Considering the empirical results from the comprehensive principal component analysis, the following policy recommendations are proposed for the current regional data input levels of the 30 provinces in China:

Formulate preferential policies: The government should establish preferential policies for the data industry, including tax exemptions, financial support, and high-quality infrastructure, to encourage enterprises and institutions to increase their investment in data input.

Enhance technological innovation capabilities: Strengthening technological innovation is a crucial way to improve data input levels. The government should increase support for scientific research and development, encourage businesses to enhance technological innovation, and improve their abilities in data analysis and mining.

Strengthen talent cultivation and recruitment: Cultivating and attracting high-quality data science and analysis professionals is essential for improving data input levels. The government and universities should enhance efforts in training professionals in the field of data science and analysis, while also encouraging the recruitment of outstanding domestic and international data scientists and analysts.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

The authors would like to acknowledge the Project "Research on the Impact of Data Elements on Regional Input-Output Efficiency in China"(2022ZXSY072), supported by Guizhou University of Finance and Economics.

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