

## *Retraction*

# **Retracted: Impact of Financial R&D Resource Allocation Efficiency Based on VR Technology and Machine Learning in Complex Systems on Total Factor Productivity**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] H. Sun and X. Zhong, "Impact of Financial R&D Resource Allocation Efficiency Based on VR Technology and Machine Learning in Complex Systems on Total Factor Productivity," *Complexity*, vol. 2020, Article ID 6679846, 15 pages, 2020.

## Research Article

# Impact of Financial R&D Resource Allocation Efficiency Based on VR Technology and Machine Learning in Complex Systems on Total Factor Productivity

Hui Sun <sup>1</sup> and Xiong Zhong <sup>2</sup>

<sup>1</sup>School of Economics and Statistics, Guangzhou University, Guangzhou 510006, Guangdong, China

<sup>2</sup>Institute of Finance, Guangzhou University (Guangzhou Institute of International Finance), Guangzhou 510006, Guangdong, China

Correspondence should be addressed to Xiong Zhong; [zhongxiong@gzhu.edu.cn](mailto:zhongxiong@gzhu.edu.cn)

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With the development of the globalization of science and technology, innovation has become an important driving force for regional economic development. As a core element of regional innovation, financial R&D resources have also become a key element to enhance national innovation capabilities and national economic competitiveness. National and regional innovation capabilities have a direct impact. There are also many deep-seated problems behind the world-renowned achievements, such as irrational industrial structure, insufficient independent innovation capabilities, low resource utilization efficiency, and the service quality and efficiency of financial institutions for the transformation of total factor productivity. These problems extremely restrict the efficiency upgrade and further development of our country's total factor productivity. This study uses the DEA-Malmquist index model to measure the efficiency of fiscal R&D resource allocation in 28 provinces and regions in China in the past 10 years and uses Mapinfo12.0 software to analyze regional differences in the efficiency of fiscal R&D resource allocation in China from a spatial perspective. During the year, the overall R&D resource allocation efficiency of 28 provinces and autonomous regions in China has shown an upward trend. The efficiency of fiscal R&D resource allocation and the concentration of financial factors have had a positive impact on total factor productivity, transform and upgrade factors, increase total factor productivity, and provide empirical evidence for building a strong country.

## 1. Introduction

**1.1. Background and Significance.** In recent years, China has been steadily increasing R&D investment to improve its own level of innovation, but R&D varies greatly between different regions. Therefore, studying the efficiency of our country's R&D resource allocation and its regional differences is of great significance for reducing the differences in the efficiency of R&D resource allocation among regions, improving total factor productivity, enhancing regional innovation capabilities, and promoting the coordinated development of regional economies. As the main force of innovation resources, the effective allocation of R&D resources is playing an increasingly important role in the

process of economic development [1]. Total productivity and economic growth are the two main driving forces of modern economic growth and are important indicators of the quality of economic growth in a country or region. In order to cope with the long-term imbalance of our country's economic growth, the overall productivity level of each region has become an important basis for measuring economic efficiency and economic growth [2].

**1.2. Related Work Research.** Domestic research on the efficiency of fiscal R&D resource allocation is mainly carried out by different regions, different industries, and different R&D entities. The stochastic boundary analysis method is

used to measure the effectiveness of R&D resources in 28 provinces and regions. The factors affecting the effectiveness of regional R&D in our country from 2014 to 2019 are analyzed. DEA model and SFA model are mainly used to study the efficiency of R&D resource allocation in various regions of our country. The conclusions are basically the same. It can be considered that in the eastern, central, and western regions of our country, the allocation efficiency of R&D resources is significantly different. In regions with better economic growth, the allocation efficiency of R&D resources may not be high. The efficiency of allocating R&D resources to economically underdeveloped regions is not necessarily low, and DEA is effective or ineffective [3].

As early as the 1960s, scholars began to pay attention to the efficiency of R&D resource allocation, using the Cobb-Douglas production function to measure the efficiency of R&D resource allocation, using only R&D stock as an input indicator, select data from 40 countries and regions from 1960 to 2000 to study the effectiveness of R&D resource allocation in each country, and analyze its influencing factors. The survey results show that per capita GDP has the greatest impact on the efficiency of R&D resource allocation, and they also have a positive impact on the efficiency of R&D allocation [4, 5].

Liu G used nonparametric production frontier methods to study the components of our country's total factor productivity growth from two different perspectives: technological contribution and factor contribution. By combining two-year environmental technology and nonradiative directional distance functions, he developed a biennial. The nonradiation direction distance function measurement can overcome the well-known infeasibility problem, incorporate the total slack of the variable, and explore the driving factors of our country's TFP. Although this growth rate has slowed down recently, our country's TFP is still growing at an annual rate of 2.02%. Secondly, from the perspective of technological contribution, technological progress is the main driving force of total factor productivity [6]. Tugcu CT studied the causal relationship between energy consumption and TFP growth in the BRIC countries. Using panel bootstrapping Granger causality test, there is no significant causal relationship between renewable energy consumption and TFP growth in BRIC countries. Concerning nonrenewable energy, there is a two-way causal relationship between Brazil and South Africa's total factor productivity growth [7].

**1.3. Innovation.** Based on the New Economic Development Theory, Resource Allocation Theory, New Economic Geography Theory, etc., this article examines the effectiveness of our country's R&D resource allocation and its spatial differences from the perspective of time and space and combines them organically. Economy and geography make it more intuitive and clear to reflect the geographical and spatial arrangement of our country's R&D activities and their temporal and spatial evolution.

In this study, the DEA-Malmquist index model and factor analysis method are used to conduct an in-depth study

of the regional differences in the effectiveness of R&D resource allocation and environmental impact factors in our country. The effectiveness of R&D allocation is broken down into technical performance and pace of technological progress, as well as regions and regions. We conduct a more thorough and specific analysis of the differences in R&D efficiency within R&D distribution and try innovative research methods.

This article is based on endogenous development theory and mathematical statistics. When estimating total factor productivity, this article uses the Cobb-Douglas production function and Malmquist index methods to cover the weaknesses of a single model in the calculation process. The overall growth rate of factors calculated by these methods is basically the same.

This paper separates the fiscal market from the financial market. When analyzing the impact of the resource allocation efficiency of the tax market on total factor productivity, it combines theoretical research with practical research, enriching the current domestic and foreign scholars' research on the impact of fiscal R&D resource allocation efficiency on total factor productivity and theoretical research on the mechanism of factor productivity.

## 2. Impact of Total Factor Productivity under Complex Systems

**2.1. Complex System.** The definition of a complex system first appeared in the American journal "Science" magazine "Complexity Album." The two authors gave the following definition: by understanding the system's subsystems, it is impossible to fully explain the nature of the system. In other words, for a complex system, its total performance is not a simple superposition of partial performance, and there is a complex nonlinear relationship between total performance and partial performance [8].

Complex systems are the main research object of complexity science, and the synchronization phenomenon of complex systems is the current research focus. When studying complex systems, complex networks are considered to be important mathematical models, and their related theories are of great significance to the study of complex systems. Durability is a key attribute of dynamic systems and is usually used to describe the dynamic behavior of spaced systems. A retrospective graph is a visualization tool based on robustness. Quantitative robustness analysis is a measure of quantitative robustness analysis [9]. As a new method of studying complex systems, retrospective graphs and quantitative reduction analysis have been widely used in many complex system problems. The logical relationship between the theories used in this article is shown in Figures 1–3.

The concept of a complex system is realized based on the critical inheritance of reductionism. The theory of complex systems is not just a refusal to restore. Reductionism is valid and logical within a certain range, because in addition to complex systems, there are other types of systems in the world. Generally, there are three types of systems in the world: simple systems, random systems, and complex systems [10].

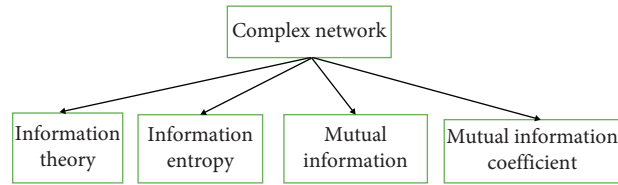


FIGURE 1: Complex system framework.

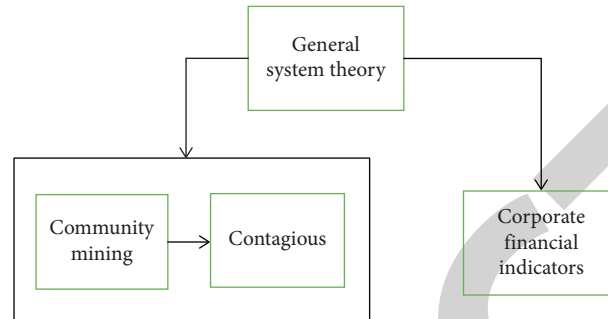


FIGURE 2: General system theory construction.

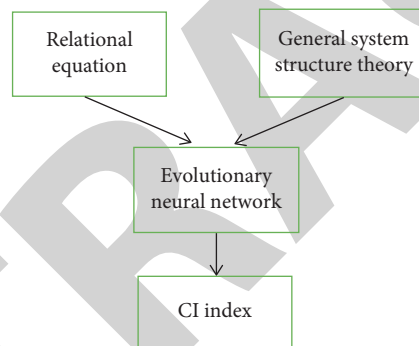


FIGURE 3: Logical relationship diagram of each theoretical tool.

A complex network is a mathematical model of a complex system. Its main purpose is to explain the existing phenomena and complexity of the network. The research object is the network [11]. The Internet is ubiquitous in nature and human society and has a profound impact on human development. Graph theory is an important tool for studying complex networks. Generally, a network is considered a graph, which contains a series of nodes and the ends that connect these nodes.

**2.2. VR Technology and Machine Learning.** VR technology is a virtual reality technology that uses computers to simulate real and unreal 3D scenes. Virtual reality technology is the highest level of current simulation and virtual reality, and it has integrated a variety of technologies, such as multimedia technology, digital image processing, sensor technology, and computer graphics [12]. VR technology can create 3D visual and sound effects. Since human-computer interaction is a friendly and harmonious state based on physical skills, 3D virtual reality technology can change the passive and boring state between man and machine. Virtual reality technology

combines computer technology, multimedia technology, image technology, simulation technology, and various electronic technologies to create new technology in the computer field, as shown in Figure 4.

Virtual reality technology is a computer simulation system that can build and experience the virtual world. Virtual reality technology is a very challenging interactive technology, which is gradually being widely used in the field of scientific research [13, 14]. At present, in the fields of military, medicine, film, and television, virtual reality technology has gradually become an important technology, and the development of virtual reality technology in the field of education is gradually deepening. Virtual reality technology is a cutting-edge technology in the computer field, which combines human-computer interaction technology, sensor technology, network technology, graphics technology, simulation technology, and stereo display technology. Virtual reality technology has three main characteristics, as shown in Figure 5.

Machine learning enables computers to learn and deal with human-like problems. Therefore, it is very important to focus on how to apply machine learning algorithms to solve

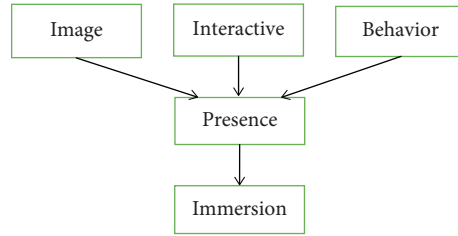


FIGURE 4: VR technology elements and characteristics.

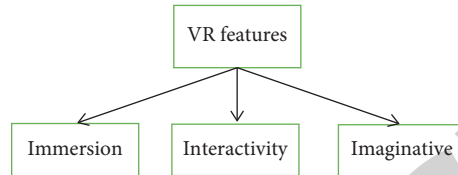


FIGURE 5: Three characteristics of virtual reality.

practical problems. Machine learning has a wide range of research scenarios and applications. It is a multidisciplinary field, including artificial intelligence, information theory, statistical probability, government, and other academic achievements [15, 16]. The machine learning algorithms involved in this research are Bayesian statistical conclusions, EM algorithms, and ADMM algorithms, as shown in Figure 6.

According to historical data, with the help of the dynamic grouping method, the indirect correlation between parameters is determined through the EM algorithm, which aims to realize the dynamic vector grouping support algorithm, which is beneficial to reduce the risk of information decision-making [17]. The specific technology application path is shown in Figure 7.

Machine learning uses detailed methods in statistics, evidence theory, neural networks, fuzzy sets, primitive sets, evolutionary computing, and other fields to complete data summarization, concept description, classification rule extraction, grouping analysis, data analysis, analysis and sequence pattern discovery, and other types of work [18, 19]. Compared with data mining, machine learning tends to provide different algorithms, while data mining tends to use these algorithms to solve problems. Common machine learning algorithms include the following categories:

- (1) Classification algorithm: representative algorithms are decision tree algorithm and a naive Bayes algorithm
- (2) Clustering algorithm: representative algorithms are K-means algorithm and EM algorithm
- (3) Association rule extraction algorithm: the representative algorithm is the Apriori algorithm
- (4) Support vector machine, namely, SVM algorithm
- (5) Neural Networks
- (6) Genetic algorithm

Logistic regression (LR) is a machine learning algorithm with low model complexity and a classic statistical

classification algorithm. Its advantages are low computational complexity, easy to understand and apply, and can be used for large-scale machine learning and online learning tasks [17]. The conditional probability distribution formula of the binomial logistic regression model is

$$P(A = 1|x) = \frac{\exp(mx + n)}{1 + \exp(mx + n)},$$

$$P(A = 0|x) = \frac{1}{1 + \exp(mx + n)}. \quad (1)$$

**2.3. Fiscal R&D Resource Allocation Efficiency.** R&D (Research and Development) refers to the human, material, and financial resources required to participate in scientific research and experimental development activities. R&D expenditure and its proportion in GDP reflect the important content of our country's independent innovation capability and the process of building an innovative country. It is an important indicator to measure the scale of a country's scientific and technological activities and the level of scientific and technological investment, and it is also an important indicator to improve our country's innovation potential and enhance the competitiveness of the national economy. UNESCO believes that R&D is a systematic creative activity that uses new knowledge to create new applications. OECD (Organization for Economic Cooperation and Development) believes that R&D is a more systematic and creative activity. This type of activity is based on increasing the total amount of knowledge and using that knowledge to create new applications [20].

Resource allocation was first proposed by the classical economy. It emphasized the role of the market in the allocation of resources and believed that the market was the most important way to allocate resources. However, in fact, due to the shortcomings of the market itself, especially the failed market, it seriously wasted resources. Adam Smith believes that due to a lack of resources, the market uses

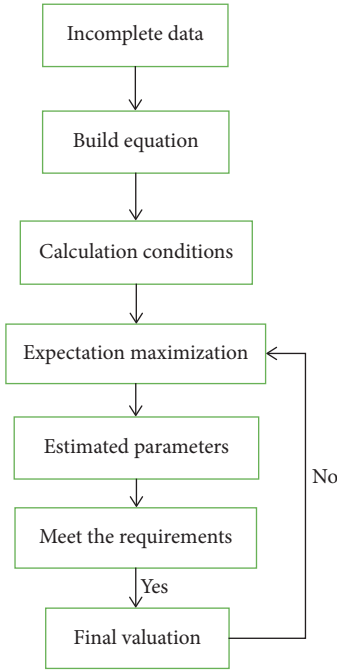


FIGURE 6: Flow chart of the EM algorithm.

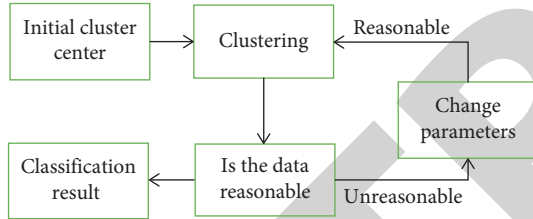


FIGURE 7: Technical route of dynamic clustering decision.

profit-driven methods to achieve effective resource allocation. Tables 1 and 2 list the average fiscal R&D resource allocation efficiency of countries and regions.

**2.4. TFP.** Total factor productivity (TFP) refers to factors other than capital and labor income that contribute to economic growth. It is an important indicator to measure the quality of economic growth. Our country has a lot of research on total factor productivity. Total factor productivity is proposed relative to the concept of single-factor productivity. After excluding the increase in input rate, the remaining contribution of production improvement sources is attributed to the improvement of technology and efficiency. This part is total factor productivity, that is, the rest of the economic growth that cannot be explained by input factors. Fundamentally speaking, total factor productivity measures the influence of factors such as technological innovation, process improvement, management level, and efficiency. The role of industrial organization in economic development reflects the quality of economic development and represents the overall efficiency of the use of input factors [21].

Comparing the differences in total factor productivity between different countries, the scale of total factor productivity will directly affect the level of economic growth. There are several methods for calculating TFP in empirical research. Solow residual algorithm will be used, and its approximate algorithm is as follows:

$$\text{TFP growth} = \frac{\dot{L}}{L} = \frac{\dot{M}}{M} - \beta \frac{\dot{N}}{N} - (1 - \beta) \frac{\dot{O}}{O}, \quad (2)$$

where  $L$  is the technology input,  $M$  is the output,  $N$  is the capital input,  $O$  is the labor input, and  $\beta$  is the proportion of capital input to output. According to the above Solow formula, if we want to be able to accurately calculate the growth of TFP, we must adopt the function of neoclassical production. The factor market is fiercely competitive, and the growth rate of various inputs must be accurate. In addition, many papers have adopted the following methods, but the basic idea is the same as the above formula:

$$\text{TFP} = \frac{M}{N^\beta \times O^{1-\beta}}. \quad (3)$$

In order to calculate total factor productivity, some documents divide the calculation methods into two categories: trend estimation method and production function method. Trend estimation methods include parametric, semiparametric, and nonparametric methods. It uses total factor productivity as the default variable and uses long-term statistical information to estimate total factor productivity based on a set of assumptions. The production function method is mainly based on the basic form of the Cobb-Douglas production function in the neoclassical development theory. It uses mathematical transformations to discover the number of factors affecting economic growth, such as technological level and technical performance, in addition to capital and labor. Therefore, the productivity of all factors can also be called the residual value of the production function [22].

This article will choose the SFA method and use the prior logarithmic function to calculate our country's interprovincial total factor productivity. The production function has the following form:

$$\begin{aligned} \ln S_{a,b} = & \alpha_0 + \alpha_1 \ln M_{ab} + \alpha_2 \ln N_{ab} + \beta_1 b \\ & + \frac{1}{2} \beta_2 \ln^2 N_{ab} + \frac{1}{2} \beta_3 \ln^2 M_{ab} \\ & + \frac{1}{2} \beta_4 b^2 + \beta_5 \ln N_{ab} M_{ab} + \beta_6 b \ln M_{ab} \\ & + \beta_7 b \ln N_{ab} + x_{a,b} - y_{a,b}. \end{aligned} \quad (4)$$

When all  $\beta$  is 0, the model will become a technically neutral Cobb-Douglas production function. In addition, the model also considers static and dynamic technological

TABLE 1: Average allocation efficiency of our country's fiscal R&amp;D resources.

Year	Technical efficiency	Technological progress rate	Pure technical efficiency	Scale efficiency	Allocation efficiency
2014	1.041	0.967	1.021	1.018	0.999
2015	0.988	1.030	0.977	1.021	1.003
2016	1.032	0.944	1.016	1.017	0.956
2017	0.999	0.947	0.966	1.052	0.955
2018	1.011	1.069	0.996	1.032	1.095
2019	1.036	0.981	1.021	1.025	1.008
Average value	1.018	0.990	1.000	1.028	1.010

TABLE 2: Average allocation efficiency of financial R&amp;D resources in each region.

Year	Technical efficiency	Technological progress rate	Pure technical efficiency	Scale efficiency	Allocation efficiency
East	0.996	1.016	0.996	1.001	1.015
Central	1.003	1.000	0.998	1.005	1.001
West	1.020	0.986	1.018	1.002	1.007

progress and the dynamic interaction of labor and capital input into production. By organization, we get

$$IHK_{ab} = IJ_{ab} + IK_{ab} + (JF - 1)(\lambda_N(\lambda_N + \lambda_M)N + \lambda_M(\lambda_N + \lambda_M)M), \quad (5)$$

and decomposing it, the production efficiency change rate is

$$IJ_a = J[\exp(-y_a)|x_a - y_a]. \quad (6)$$

The technical progress rate is

$$IK_{ab} = \frac{\partial \ln S_{ab}}{\partial} = \beta_1 + \beta_4 b + \beta_6 \ln m_{ab} + \beta_7 \ln n_{ab}. \quad (7)$$

The rate of change of scale efficiency is

$$FJC = (JF - 1) \left( \frac{\mu_N}{\mu_N + \mu_M} \times N + (\mu_N + \mu_M)M \right). \quad (8)$$

Among them,  $\mu_N$  and  $\mu_M$ , respectively, represent the output elasticity of capital and labor relative to the overall return to scale:

$$\begin{aligned} \mu_N &= \alpha_N + \beta_7 b + \beta_5 \ln M_{ab} + \beta_2 \ln N_{ab}, \\ \mu_M &= \alpha_M + \beta_6 b + \beta_5 \ln N_{ab} + \beta_3 \ln M_{ab}. \end{aligned} \quad (9)$$

**2.5. Model Building.** In this study, the DEA-Malmquist index model was used to measure the effectiveness of R&D allocation in our country. In the DEA empirical research, in order to reflect the evolution of production unit efficiency in different periods, the most widely used production efficiency index is the Malmquist index [23]. Caves proposed that under multiple inputs and outputs, the total productivity based on the input data can be expressed by the Malmquist index. In order to obtain the Malmquist efficiency value, the distance function  $S^a(x_0^a, y_0^a)$  needs to be input, which is the inverse of the input efficiency, namely,

$$S^a(x_0^a, y_0^a) = \frac{1}{T^a(y_0^a, x_0^a)}. \quad (10)$$

This function is the smallest degree where  $x_0^a$  can be reduced under a given  $y_0^a$ . When

$$S^a(x_0^a, y_0^a) = 1, \quad (11)$$

$(x_0^a, y_0^a)$  on the frontier of production,

$$S^a(x_0^a, y_0^a) > 1 \quad (12)$$

indicates that the technology is invalid, and the performance value can be expressed by the Malmquist index:

$$T^a = \frac{S^a(x_0^a, y_0^a)}{S^a(x_0^{a+1}, y_0^{a+1})}, \quad (13)$$

$$T^{a+1} = \frac{S^{a+1}(x_0^a, y_0^a)}{S^{a+1}(x_0^{a+1}, y_0^{a+1})}.$$

These two indicators are the Malmquist index in the period  $a$  and period  $a + 1$ , respectively. We use the geometric mean of these two Malmquist indices to calculate the change in productivity, namely,

$$\begin{aligned} TI &= \frac{S^a(x_0^a, y_0^a)}{S^{a+1}(x_0^{a+1}, y_0^{a+1})} \left[ \frac{S^{a+1}(x_0^{a+1}, y_0^{a+1})}{S^a(x_0^{a+1}, y_0^{a+1})} \times \frac{S^{a+1}(x_0^a, y_0^a)}{S^a(x_0^a, y_0^a)} \right]^{1/2} \\ &= EF \times AC. \end{aligned} \quad (14)$$

$TI > 1$  shows that the productivity of the period  $t + 1$  is higher than the productivity of period  $a$ . Malmquist index can be decomposed into technical performance index and technological progress rate index. EF and AC are greater than, equal to, and less than 1, respectively, indicating that the technical performance and technological progress rate remain unchanged or decline, and the technical efficiency is

decomposed into pure technical efficiency index and index scale efficiency. The survey is used to measure the changes in the effectiveness of R&D allocation in 28 provinces and regions in our country from 2014 to 2019 [24].

A general method of estimating capital stock and current capital is the sum of current new capital investment and previous capital minus capital depreciation. The basic types of calculations are

$$R_x = \frac{A_x}{B_x} + (1 - \mu)R_{x-1}. \quad (15)$$

Among them,  $R$ ,  $A$ , and  $B$  are the capital stock, investment, and fixed asset investment price index,  $\mu$  is the annual depreciation rate of capital, and the subscript  $x$  represents the period [25].

### 3. Experiment on the Influence of Total Factor Productivity under Complex Systems

A large number of research results show that the efficiency of fiscal R&D resource allocation is a key factor in promoting overall productivity and economic growth. Comparing the results of different empirical methods, we can conclude that the massive influx of R&D funds based on international trade has greatly increased the overall factor productivity of our country's industry, while the low efficiency of domestic fiscal R&D resource allocation has restricted its growth. Therefore, it is recommended to improve the efficiency of fiscal R&D resource allocation and strengthen trade with developed countries.

**3.1. Test Subject.** The empirical part of this article first examines the direct impact of R&D resource allocation efficiency on improving the overall productivity of participants. In addition, in order to further determine the impact mechanism, this article decomposes the overall productivity of agents into changes in technical progress (TE) and technical efficiency (EF). Conversely, as explained by the variables, it empirically examines the impact of R&D resource allocation efficiency on technological progress and technical efficiency. Therefore, this paper constructs the following model with total factor productivity (TFP) as a variable explanation:

$$\begin{aligned} TFP_{ab} = & \omega + \lambda_1 TFP_{ab-1} + \lambda_2 FA_{ab-1} + \lambda_3 RND_{ab} + \lambda_4 HC_{ab} \\ & + \lambda_5 GI_{ab} + \lambda_6 FDI_{ab} + \lambda_7 OPEN_{ab} + \lambda_8 DAR_{ab} + z_{ab}. \end{aligned} \quad (16)$$

**3.2. Test Design.** Total factor productivity is the main indicator to measure the impact of resource allocation efficiency and technological innovation level on economic growth. In order to be able to estimate total factor productivity, we introduced the Cobb-Douglas (CD) production function into the analysis process based on the practice of other scholars. The production function is as follows:

$$S_{ab} = L_{ab} M_{ab}^\alpha N_{ab}^\beta, \quad (17)$$

where  $S_{ab}$  represents the GDP of province  $a$  in year  $b$ ,  $L_{ab}$  represents the total factor productivity of province  $a$  in year  $b$ , and  $M_{ab}N_{ab}$  represents the capital stock and labor force of province  $a$  in year  $b$ .  $\alpha$  and  $\beta$ , respectively, represent the output elasticity of the two production factors of capital and labor. Taking the logarithm of both sides of the formula equation at the same time, you can get

$$\ln S_{ab} = \ln L_{ab} + \ln M_{ab} + \ln N_{ab}. \quad (18)$$

Doing further transformation, you can get

$$\ln L_{ab} = \ln S_{ab} - \ln M_{ab} - \ln N_{ab}, \quad (19)$$

where  $\ln L_{ab}$  is the logarithm of the total factor productivity of each province over the years. Taking the physical indicators on the left and right sides of the equation at the same time, we can get the final expression of total factor productivity:

$$\ln L_{ab} = \exp(\ln S_{ab} - \ln M_{ab} - \ln N_{ab}). \quad (20)$$

We use the Solow residual method to decompose and measure total factor productivity and set the total production function as the C-D production function:

$$G_a = X e^{\lambda a} Y_a^\alpha Z_a^\beta. \quad (21)$$

Among them,  $G_a$  is the actual output,  $Z_a$  is the labor input,  $Y_a$  is the capital stock, and  $\alpha, \beta$  are the average labor output share and the average capital output share, respectively.

Now, we make the following assumptions: constant returns to scale; if the input quantity increases by the same percentage, the output also increases by the same percentage; the neutral technology assumes that labor productivity and capital productivity increase by the same percentage; the natural logarithm of the two sides is as follows:

$$\ln(G_a) = \ln(X) + \lambda a + \alpha \ln(Y_a) + \beta \ln(Z_a). \quad (22)$$

The growth rate of total factor productivity is derived as

$$\frac{\Delta X}{X} = \frac{\Delta G}{G - (1 - \alpha)} \times \frac{\Delta Z}{Z} - \alpha \times \frac{\Delta Y}{Y}. \quad (23)$$

Under the constraint condition  $\alpha + \beta = 1$  of constant return to scale, we have

$$\ln\left(\frac{G_a}{Z_a}\right) = \ln(X) + \lambda a + \alpha \ln\left(\frac{Y_a}{Z_a}\right). \quad (24)$$

After estimating the average share of capital production and labor productivity, the growth rate of total factor productivity can be obtained by introducing equations. We judge  $\alpha = 0.7, \beta = 0.3$  according to the empirical method and bring the total factor productivity table.



## 4. Impact on Total Factor Productivity

*4.1. Time Series Changes in the Efficiency of Fiscal R&D Resource Allocation.* As shown in Figure 8, the TFP growth rate of the entire industry from 2014 to 2019 was 8.4%, the average growth rate of technical performance was  $-1.4\%$ , and the average growth rate of technological progress was  $9.9\%$ . Technological progress plays a leading role in changes in total factor productivity. The contribution of technological progress to the overall productivity growth of the industry is far greater than changes in technical performance. Further analysis of the net changes in technical performance and scale performance changes of EF decomposition elements shows that my country as a whole has reduced the return to scale ( $-2.4\%$ ). The speed of technological progress is a key factor that affects the efficiency of R&D resource allocation. On this basis, the factor analysis method is used to analyze the environmental factors that affect the efficiency of R&D resource allocation. The research results show the government support, economic development level, and foreign investment level. It plays an important role in promoting my country's total factor productivity and is also an important reason for regional differences, as shown in Table 3.

As shown in Figure 9, the change in the efficiency of my country's fiscal R&D resource allocation is almost the same as the change in the pace of technological progress, while pure technical efficiency and scale performance have little effect on the efficiency of R&D allocation, indicating that technological progress at this pace directly affects the allocation of R&D resources. The overall efficiency of efficiency, the level of research, and development need to be improved. The efficiency of resource allocation must be based on the perspective of technological progress. As shown in Table 4, the rapid improvement of technological level, the renewal of technical equipment, technological innovation, and the introduction of advanced technology have a greater impact on improving the efficiency of my country's R&D resource allocation.

As shown in Figure 10, from 2014 to 2019, my country's overall resource allocation for fiscal research and development showed a slow growth trend, with an average rate of return of 1.01, but the growth rate was very slow. During these 7 years, the average growth rate of my country's R&D resource allocation efficiency was only  $0.5\%$ , which was mainly attributed to the slight increase in the rate of technological progress during the research period. In addition, the resource allocation efficiency of R&D reached the highest level in 2018, mainly due to the greatly improved technical level and the acceleration of technological progress. As shown in the figure, the slowing rate of technological progress has led to a decrease in the efficiency of R&D distribution, which is different in 2015 and 2018. The growth rate in 2016 has slightly decreased, as shown in Table 5.

*4.2. Regional Differences in the Efficiency of Fiscal R&D Resource Allocation.* As shown in Figure 11, in order to facilitate the analysis of regional differences in the efficiency of

my country's fiscal R&D resource allocation, this study divides my country's 30 provinces into eastern, central, and western regions. The R&D resource cost-sharing rate and national change coefficient of 30 provinces in eastern, central, and western regions of my country from 2000 to 2012 are given. The distribution efficiency of R&D resources in the eastern and central regions has shown a downward trend, while the western region has shown an upward trend.

As shown in Table 6, from the overall level, the efficiency of R&D resource allocation in each region is characterized by the highest in the east, the second in the west, and the lowest in the middle. The average efficiency is 1.014, 1.004, and 1.000 in order. The R&D distribution efficiency in the eastern region is 1.005 higher than the national average, and the central and western regions are lower than the national average. The coefficient of variation of the national average rate of return on R&D resources shows a downward trend, indicating that the regional differences in the efficiency of R&D resource allocation in my country are generally shrinking, as shown in Figure 12.

*4.3. Overall Situation of Total Factor Productivity.* As shown in Figure 13, total factor productivity decreased significantly from 2000 to 2016, and total factor productivity increased significantly from 2013 to 2014. This fully shows that my country's deepening reform and opening-up have led to economic growth and total factor productivity. Total factor productivity reached its peak in almost every city in 2014 and then declined every year. This shows that reform and opening-up can indeed bring technological progress and increase overall factor productivity, but with the past of reform and opening-up, this impact will continue to weaken, as shown in Table 7.

As shown in Figure 14, from a national level, the overall factor productivity generally declined. From 2010 to 2019, the growth rate of the total factor productivity in most cities was less than zero in most years. This shows that my country's economic growth is highly dependent on capital and labor, and my country's technological progress is not obvious. On average, my country's major cities have shrunk by  $5.78\%$ . During these years, the total factor productivity of 41% of the cities increased in 2010, which was the best year for total factor productivity. However, the overall factor productivity in 2015, 2018, and 2019 showed an overall downward trend. Almost 95% of cities showed negative growth in all factors.

*4.4. TFP and Decomposition Index.* As shown in Figure 15, using DEAP2.1 software, we select the input-oriented fixed income statement model and use table data from 30 provinces to obtain the results of the Malmquist index method. The Malmquist index decomposition model provides a comprehensive performance index for the total factor productivity of each province in my country. The index can be decomposed into the rate of scale efficiency change and the net change of technical performance according to the rate of change of technical performance, the rate of technological progress, and the rate of change of technical

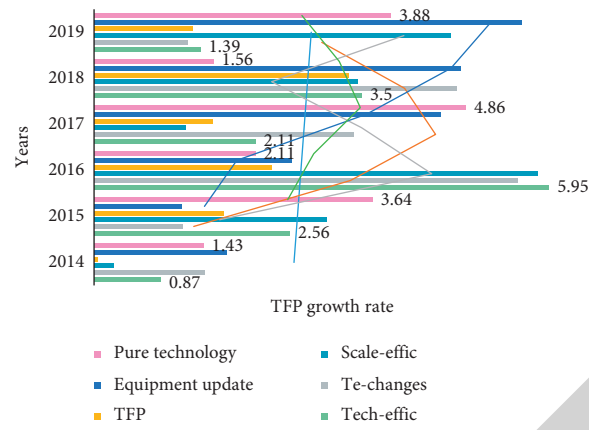


FIGURE 8: Net changes in technical performance and changes in scale performance.

TABLE 3: 2014–2019 total factor productivity index.

Year	Technical efficiency changes	Technological progress changes	Scale efficiency changes	TFP
2014	1.101	0.987	1.070	1.086
2015	0.925	1.236	0.945	1.142
2016	0.886	1.135	0.905	1.006
2017	1.014	1.041	1.001	1.055
2018	0.988	1.038	0.999	1.025
2019	1.005	1.028	1.002	1.032
Average	0.987	1.078	0.987	1.058

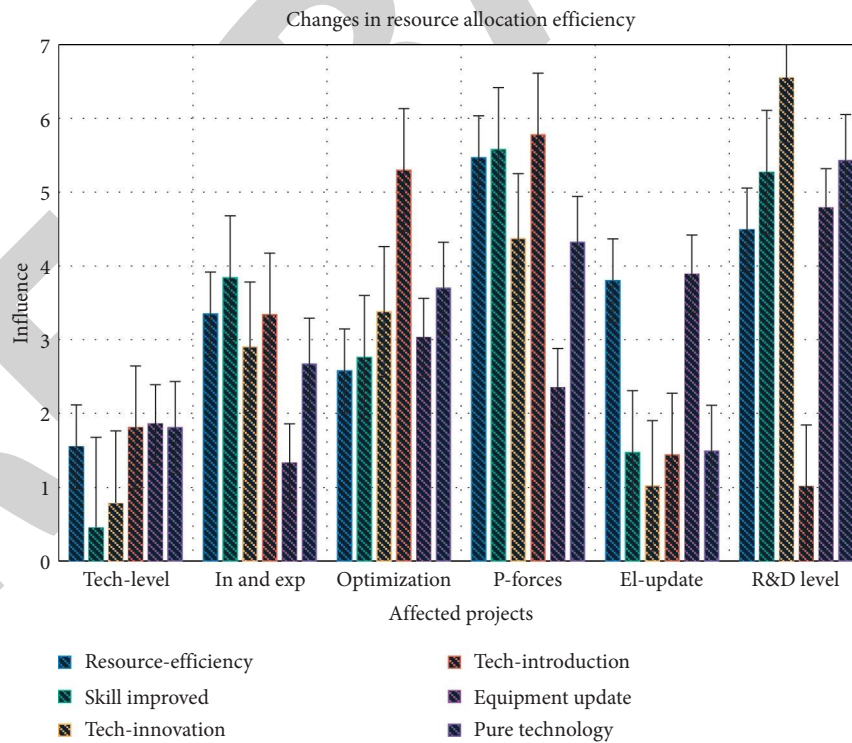


FIGURE 9: Relationship between changes in resource allocation efficiency.

TABLE 4: R&D resource allocation efficiency has a greater impact.

Item	Resource-efficiency	Innovation	Skill	Introduction	Equipment	Pure
Tech-level	1.55	0.78	0.45	1.81	1.86	1.81
In and exp	3.35	2.9	3.84	3.34	1.33	2.67
Optimization	2.58	3.38	2.76	5.3	3.03	3.7
P-forces	5.47	4.37	5.58	5.78	2.35	4.32
El-update	3.8	1.02	1.47	1.44	3.89	1.49
R&D level	4.49	6.55	5.27	1.01	4.79	5.43

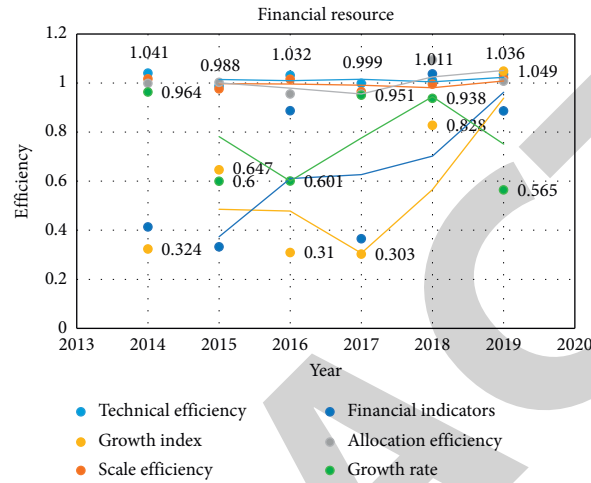


FIGURE 10: The efficiency of financial resource allocation in recent years.

TABLE 5: Decreased rate of technological progress leads to lower R&D distribution efficiency.

Item	Technical efficiency	Scale efficiency	Allocation efficiency	Growth index	Financial indicators	Growth rate
2014	1.041	1.018	0.999	0.362	0.403	0.708
2015	0.988	0.977	1.003	1.081	0.454	0.849
2016	1.032	1.016	0.956	0.796	0.743	0.651
2017	0.999	0.966	0.955	0.827	0.666	0.41
2018	1.011	0.996	1.095	0.348	0.999	0.354
2019	1.036	1.021	1.008	0.488	0.566	0.313

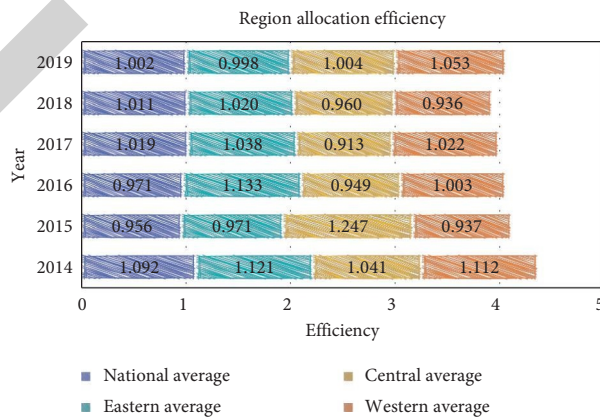


FIGURE 11: Changes in the efficiency of regional fiscal R&D resource allocation.

TABLE 6: R&D resource allocation efficiency in various regions.

	Distribution rate	Allocation efficiency	Response rate	Mean efficiency	R&D rate	Factors of production
East	1.84	0.34	1.88	0.94	1.84	0.67
West	1.52	2.79	3.84	3.19	3.57	2.7
Central	2.96	4	3.36	5.07	4.46	3.53
South	2.25	2.66	2.74	4.66	1.51	4.75
North	2.98	1.64	1.78	1.58	1.58	2.49

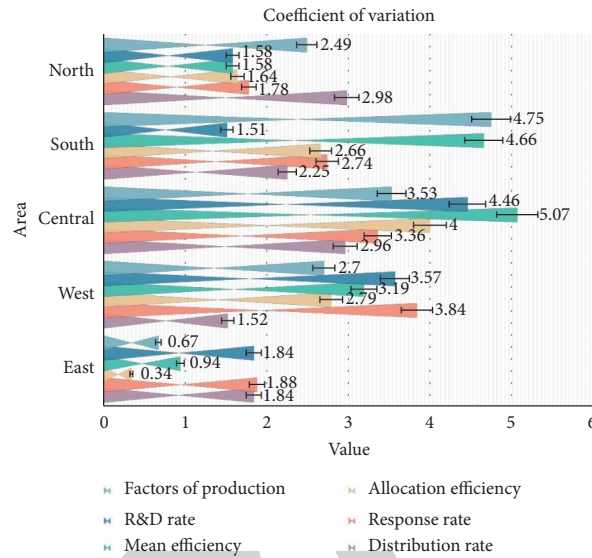


FIGURE 12: Coefficient of variation of the average rate of return on national R&D resources.

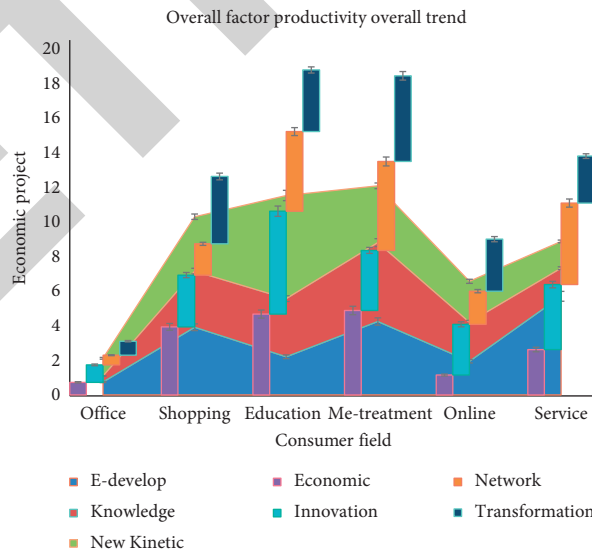


FIGURE 13: Overall factor productivity overall trend.

performance rate. As shown in Table 8, from 2014 to 2019, my country's total factor productivity increased by 4.02% annually, net efficiency changed (-0.37%), net technological progress changed (3.91%), scale efficiency changed (-0.08%), and technology scale changed (-0.37%).

Technological progress is the main factor leading to the increase in green total factor productivity. The regional differences in my country's green factor productivity growth are very obvious. From east to west, there is a gradual downward trend. From 2014 to 2019, the average annual

TABLE 7: The influence of total factor productivity.

E-Item	E-develop	New kinetic	Knowledge	Economic	Innovation	Network	Transformation
Office	0.75	1.02	0.35	0.73	1.01	0.56	0.81
Shopping	3.92	3.15	3.25	3.94	3	1.81	3.9
Education	2.21	5.97	3.37	4.68	5.96	4.61	3.57
Me-treatment	4.25	3.29	4.57	4.89	3.48	5.15	4.96
Online	1.95	2.37	2.26	1.15	2.94	1.92	3.01
Service	5.71	1.55	1.63	2.63	3.76	4.72	2.72

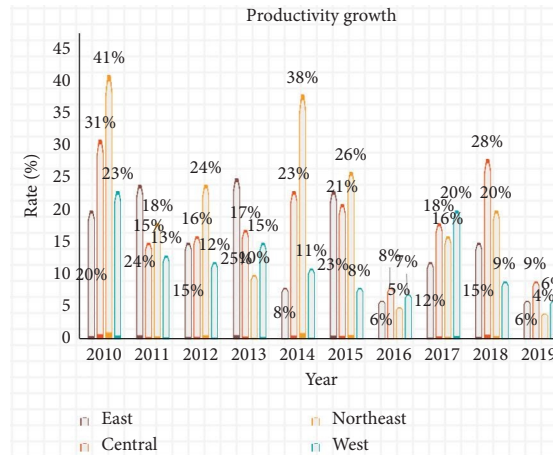


FIGURE 14: Proportion of cities with total factor productivity growth in each region.

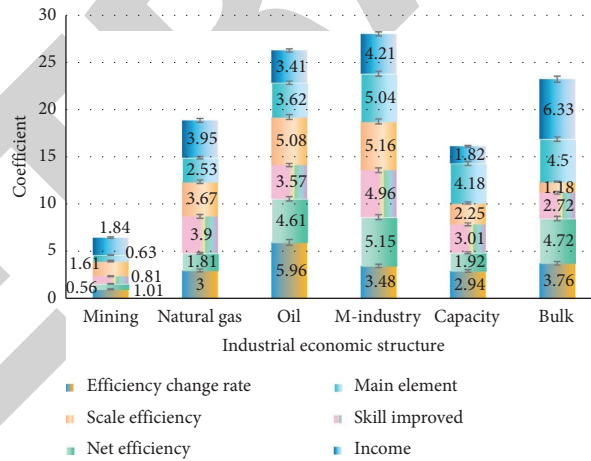


FIGURE 15: Results of the Malmquist index method.

growth rate of total factor productivity in the eastern region was 5.56%, the central region was 3.60%, and the western region was 2.79%, as shown in Table 9.

4.5. Calculation and Analysis of TFP in the East, Middle, and West. As shown in Figure 16, in order to avoid duplication of the work of this article when analyzing the TFP differences in the three main regions of eastern, central, and western regions, this article studies the differences in these three regions based on the results of the Malmquist index calculation method. In order to visually see the

changes in total factor productivity in the three main regions, the average total factor productivity value of each region and province is used. In the case of subregional levels, the overall growth rate of agents in the eastern region is the fastest. Secondly, the overall growth rate of agents in the central region is usually higher than that in the western region.

As shown in Figure 17, the development of total factor productivity in these three regions from 2004 to 2009 was mainly attributed to technological progress. After 2009, this is the result of the comprehensive influence of technological

TABLE 8: The index is based on the rate of change of technical performance.

Item	Efficiency change rate	Net efficiency	Skill improved	Scale efficiency	Main element
Mining	1.01	0.56	0.81	1.61	0.63
Natural gas	3	1.81	3.9	3.67	2.53
Oil	5.96	4.61	3.57	5.08	3.62
M-industry	3.48	5.15	4.96	5.16	5.04
Capacity	2.94	1.92	3.01	2.25	4.18
Bulk	3.76	4.72	2.72	1.18	4.5

TABLE 9: Economic implications of TFP and its breakdown indicators.

Index	Economic implications	>0	<0
TFP	Total factor productivity after deducting environmental costs	Total factor productivity growth	Green total factor productivity decline
Pure efficiency change	Management innovation, system innovation Induced productivity changes	Pure efficiency improvement	Pure efficiency deterioration
Pure technological progress	Technological innovation, process improvement Induced productivity changes	Pure technological progress	Pure technology regression
Scale efficiency changes	Productivity changes caused by economies of scale brought about by scale expansion	Increased scale efficiency	Scale efficiency decline
Technological scale changes	It only represents the technical meaning of DEA, not the economic meaning	Technology deviation from CRS	Technology deviation from VRS



FIGURE 16: Average TFP of east, mid, and west.

progress and technical efficiency, making total factor productivity an annual trend. After 2000, the macroeconomy entered a stage of improvement. The technological progress in the eastern region has always been higher than that in the central and western regions, followed by the technological progress in the central region, and the lowest in the western region. This is the result of the spread of technological

progress. While taking advantage of the geographical advantages of the neighboring eastern region, the central region of my country must introduce advanced technologies, maintain technological progress, and at the same time pay attention to improving technical efficiency to more effectively promote the development of total factor productivity, as shown in Table 10.

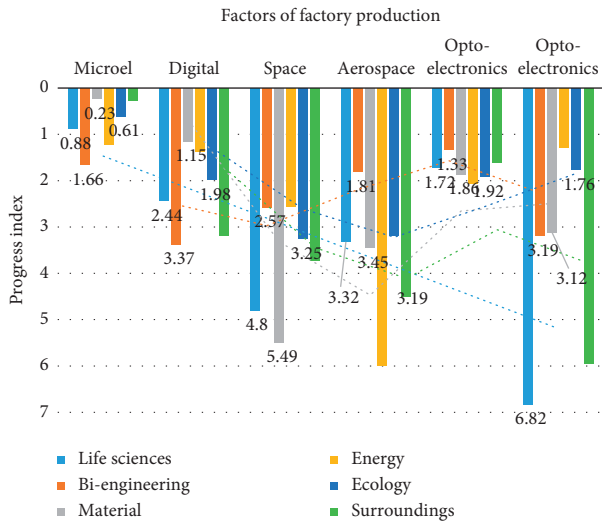


FIGURE 17: The macroeconomy has entered an improvement stage.

TABLE 10: Differences in TFP between the three main regions in the central and western regions.

Years	East	Central	West	South	North
2000	0.968	2.31	0.958	3.5	1.87
2008	1.31	1	0.49	1.2	2.58
2009	2.3	3.7	1.62	3.44	4.61
2012	2.42	3.98	2.22	3.8	2.99
2014	5.24	4.65	1.56	1.71	4.89
2016	3.48	4.31	4.35	4.18	3.26
2019	3.97	4.02	4.59	6.51	3.2

### 5. Conclusion

In the short term, the efficiency of fiscal R&D resource allocation promotes the development of total factor productivity, but as time goes by, its effect weakens. TFP limits the quality of economic growth in the short term, and the long-term effect of promoting the quality of economic growth tends to increase; during the inspection period, the economic growth rate is restricted. Among the three economic growth variables studied, the speed of economic growth has the greatest impact on the quality of economic growth. Therefore, at this stage, our country should control the rate of economic growth, improve the rationality of the allocation of R&D resources, promote the growth of total factor productivity, and achieve a slowdown in economic growth and high-quality growth.

Improving the quality of total factor productivity and economic growth will in turn help the rational allocation of fiscal R&D resources. The impact of economic growth on this has changed from positive to negative, which indicates that the excessive pursuit of economic growth will be ignored. This shows that excessive pursuit of economic growth will be ignored and to a certain extent will lead to waste of resources. The quality of economic growth has a deterrent effect on total factor productivity in the short term, but in the long run, it has an increasingly stronger role in promoting total factor productivity. Among these three variables, the

quality of economic growth has an effect on total factor productivity, which is the greatest contribution. Therefore, our country's pursuit of low-speed, high-quality economic growth can feedback the rational allocation of fiscal R&D resources and the development of total factor productivity, which forms a virtuous circle of economic activities.

If our country blindly pursues economic growth at the expense of the environment and resource waste, it will lead to a shortage of various social and natural resources, which will lead to a financial crisis, inflation, weak economic growth, and even serious problems. Excessive pursuit of the quality of economic growth requires increasing welfare benefits, increasing the cost of controlling environmental pollution, and shutting down a large number of seriously polluting enterprises. This poses a huge challenge to our country's fiscal expenditure capacity and leads to a slowdown in economic growth. Therefore, the relationship between the two must be properly handled to ensure healthy and stable economic growth.

### Data Availability

No data were used to support this study.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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