# Using data envelopment analysis to assess innovation paths in technology transfer models

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**Abstract** In recent years, technology transfer in China's provinces and regions has shown an imbalanced situation, and technology transfer efficiency has become an important indicator for measuring regional innovation capacity. This study uses data envelopment analysis to construct a technology transfer efficiency evaluation system, measures and dynamically analyzes the technology transfer efficiency of 30 Chinese provinces and regions based on the BCC model and Malmquist index, and explores the influencing factors using RF regression and Tobit regression. The results show that: the average comprehensive efficiency of technology transfer in Chinese provinces and regions is 0.876, among which 12 provinces and regions' comprehensive efficiency of technology transfer reaches DEA effective, accounting for 40%; 18 provinces and regions' technical efficiency reaches DEA effective, accounting for 60%; and 12 provinces and regions' scale efficiency reaches effective, accounting for 40%.In 2018-2024, China's technology transfer's Malmquist index is 0.96, showing a decreasing trend, and the decrease in the average efficiency of technology transfer is mainly constrained by the technical progress index (0.966). Regression analysis shows that new product sales revenue is the most significant factor affecting the efficiency of technology transfer. The study proposes that for provinces and regions with different efficiency levels, collaborative innovation development strategies should be adopted to optimize the industrial structure, rationally allocate R&D resources, and establish a sound technology transfer service system, so as to enhance the regional technology transfer efficiency and innovation capacity.

**Index Terms** technology transfer efficiency, data envelopment analysis, Malmquist index, comprehensive efficiency, collaborative innovation, significant factors, industrial structure

## I. Introduction

Science and technology play a prominent role in enhancing national competitiveness and promoting economic development and social progress. If we want to give full play to its role, the most important thing is to transform these science and technology into actual productivity, only into actual productivity, countries and enterprises can make full use of it, so as to promote their own development and enhance competitiveness [1]-[3].

However, with the development of economic globalization, the competition among countries is becoming more and more intense, and the demand for innovative technology is gradually increasing, especially for developing countries whose technological innovation is difficult to surpass that of developed countries [4], [5]. And the development of the country can not be separated from the development of enterprises, without the support of innovative technology, enterprises are difficult to compete with other enterprises with high and new technology, so enterprises are in urgent need of high and new technology support [6].

At the international level, if the scientific and technological achievements can be transformed into technologies that can be used by enterprises through certain means, this can ensure that the output of scientific and technological achievements can be transformed into practically usable resources, thus providing enterprises with high and new technologies, improving their own advantages, and enhancing competitiveness [7]-[10]. In addition, technology transfer builds a bridge between universities and academic circles and private sectors such as enterprises, so that the two can carry out more in-depth and professional exchange of scientific and technological information, which also makes high-tech research and development results can be better and faster applied to society [11]-[13].

However, in the current situation, the scientific and technological achievements produced by universities and other organizations have not been completely transformed into enterprises, and most of the scientific and technological achievements have not been effectively transformed, resulting in the waste of scientific and technological achievements [14], [15]. Therefore, it is necessary to explore the reasons for the low efficiency of technology transfer by evaluating the technology transfer model and promote the innovation of technology transfer path.

Technology transfer, as an important way of cross-regional flow of innovation factors, is of great significance in promoting regional synergistic development and enhancing the overall national innovation capacity. At present, global innovation competition is becoming increasingly fierce, technological barriers between countries are increasing, and countries have regarded technology transfer as a strategic fulcrum to enhance national competitiveness. China's regional development imbalance is still prominent, and there are obvious gaps between the eastern coastal regions and the central and western regions in terms of scientific and technological resources, innovation capacity, etc., which leads to obvious differences in the efficiency of inter-regional technology transfer, and restricts the coordinated development of the national innovation system as a whole. Technology transfer efficiency is an important indicator for measuring regional innovation capacity and resource allocation level, and scientific assessment of technology transfer efficiency is of great practical significance for formulating differentiated policies and promoting regional collaborative innovation. Scholars at home and abroad have mainly focused on the construction of evaluation index system, analysis of influencing factors, and exploration of optimization paths in the study of technology transfer efficiency. In terms of evaluation methods, DEA model, SFA model, principal component analysis, etc. are mainly used, but most of these studies are limited to static analysis and lack the examination of dynamic changes in technology transfer efficiency; in terms of influencing factors research, the existing literature focuses on factors of a single dimension and lacks systematic analysis; in terms of optimization paths, most of them put forward general suggestions and lack differentiated strategies for regions with different efficiency levels. Therefore, how to scientifically assess China's regional technology transfer efficiency, deeply analyze its dynamic characteristics and influencing factors, and propose targeted optimization paths has become a problem to be solved in theory and practice.

This study innovatively combines the BCC model and the Malmquist index, constructs a methodology system combining static measurement and dynamic evaluation of technology transfer efficiency, and comprehensively evaluates the technology transfer efficiency of 30 provinces and regions in China. The key influencing factors of technology transfer efficiency are systematically analyzed through mutual verification of RF regression and Tobit regression. On this basis, according to the efficiency performance of different provinces and regions, differentiated strategies such as collaborative innovation development, adjustment of industrial structure, and rational allocation of R&D resources are proposed to provide targeted suggestions for enhancing regional technology transfer efficiency, with a view to providing theoretical support and policy reference for the coordinated development of regional innovation in China.

## II.    Research methodology

### II. A.Data Envelopment Analysis Model

Currently, research methods about technology transfer mainly include data envelopment analysis (DEA) model, frontier estimation (SFA), principal component analysis, GMM estimation, Malmquist index method, etc. DEA model, as a common and commonly used efficiency measurement method, is different from the SFA model that requires large-scale samples, does not need to do parameter estimation and standardization of data, and can weaken the the influence of subjective factors, and it is more convenient to be applied to multi-output situations as it is measured based on a limited sample [16]. In view of this, this paper uses the DEA model to measure the efficiency of regional technology transfer in China.

According to the different assumptions, DEA model can be divided into CCR model and BCC model [17], the former is the most widely used model in the DEA methodology, which mainly deals with the evaluation of the relative effectiveness of decision-making units under the assumption of "constant returns to scale". Technology transfer activities have obvious characteristics of the knowledge economy, and the special nature of knowledge to a certain extent offsets the law of diminishing marginal returns of traditional factors of production, thus causing uncertainty in the marginal returns of technology transfer in different provinces and regions. Therefore, this paper adopts the BCC model to evaluate the efficiency of technology transfer in different provinces and regions of China under the assumption of changes in returns to scale, and analyzes in depth the effectiveness and returns to scale of technology transfer in Chinese provinces and regions.

The model assumes that there are $n$ decision units $DMU_j (j = 1, \cdots, n)$ and each $DMU$ has $m$ inputs and $s$ outputs, i.e., $X_j = (x_1 j, x_{2j} \cdots, x_{mj})^T, Y_j = (v_{1j}, y_{2j} \cdots, y_{sj})^T$ so that the computation of the efficiency of the $j_0$ th decision unit $DMU_{je}$ can be transformed into a fractional planning problem:

$$
\begin{cases}
\max h_0 = \dfrac{\displaystyle\sum_{r=1}^{s} u_r y_{rj_0}}{\displaystyle\sum_{i=1}^{m} v_i x_{ij_0}} \\[2em]
s.t. \dfrac{\displaystyle\sum_{r=1}^{s} u_r y_{rj}}{\displaystyle\sum_{i=1}^{m} v_i x_{ij}} \leq 1; j = 1,\cdots,n \\[2em]
u_r \geq 0, v_i \geq 0; r = 1,\cdots,s; i = 1,\cdots,m
\end{cases}
\tag{1}
$$

where, $h_0$ is the efficiency value of the $j_0$ nd decision unit, $v = (v_1, v_2, \cdots, v_m)^T$ and $u = (u_1, u_2, \cdots, u_s)^T$ are the weight coefficients of the $m$ inputs and $s$ outputs respectively.

The model in fractional form can be reduced to equivalent linear programming by Charnes-Cooper transformation and introducing non-Archimedean infinitesimals:

$$
\begin{cases}
\min[\theta - \varepsilon(e^{\wedge T} s_i^- + e^T s_r^+)] \\[1em]
s.t. \displaystyle\sum_{j=1}^{\pi} \lambda_j x_{ij} + s_i^- = \theta x_{ij_0} \\[1.5em]
\displaystyle\sum_{j=1}^{\pi} \lambda_j y_{rj} + s_i^+ = y_{rj_0}; j = 1,\cdots,n \\[1.5em]
\lambda_i \geq 0; s_i^- \geq 0, s_r^+ \geq 0; i = 1,\cdots,m; r = 1,\cdots,s
\end{cases}
\tag{2}
$$

where, $\varepsilon$ is the non-Archimedean infinitesimal quantity, $e^{\wedge} = (1,1,\cdots,1)^T \in E^m; e = (1,1,\cdots,1)^T \in E^s$. $E^m$ is the unit vector of the input indicator, $E^s$ is the unit vector of the output indicator, and $s_i^-, s_i^+$ is the slack variable. $\theta$ is the effective value of the decision unit, and $\lambda_i$ is the weighting coefficient, reflecting $DMU_{j0}$ the lowest value that can be achieved by reducing all inputs in the same proportion while keeping outputs unreduced.

### II. B.Malmquist-Luenberger exponential modeling

In order to analyze the dynamics of regional technology transfer efficiency values, this paper uses the Malmquist index, which can be decomposed into the technical efficiency index ($EC$) and the technical progress index ($TC$), and under the assumption of constant returns to scale, the technical efficiency can be decomposed into the pure technical efficiency ($PEC$) and the efficiency of scale ($SEC$) [18], namely:

$$
EC = PEC \times SEC
\tag{3}
$$

$$
\begin{aligned}
MI &= \sqrt{\left[\frac{E^t(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)} \times \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^{t+1}(x^t, y^t)}\right]} \\[1em]
&= \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)} \times \sqrt{\left[\frac{E^t(x^{t+1}, y^{t+1})}{E^{t+1}(x^{t+1}, y^{t+1})} \times \frac{E^t(x^t, y^t)}{E^{t+1}(x^t, y^t)}\right]} \\[1em]
&= EC \times TC \\
&= PEC \times SEC \times TC
\end{aligned}
\tag{4}
$$

where $M$ is the Malmquist index. $M$ Index > 1 indicates an increase in total factor productivity from the previous period and vice versa. $EC>1$, indicates an increase in technical efficiency. $TC>1$, indicates that technological progress has been made.

## III.  Indicator design and data sources

### III. A.  Indicator design

The efficiency of technology transfer encompasses multiple inputs and multiple outputs, and requires the selection of both input and output indicators. Among them, inputs are generally categorized into personnel inputs and capital inputs, while outputs are generally categorized into patent outputs and economic outputs. The study takes research and development (R&D) personnel, full-time equivalent of R&D personnel, scientific and technological activity personnel, internal expenditure of R&D funds, expenditure of funds for new product development, expenditure of funds for technological transformation and expenditure of funds for technology introduction as input indicators. The number of patent applications, the number of invention patents, the number of effective invention patents, the amount of contracts in the geographical area of technology export in the technology market as well as the number of contracts, the sales revenue of new products, the export value of new products, and the income from the main business, etc. are taken as the output indicators. China's technology transfer efficiency measurement index system is shown in Table 1.

Table 1: China's technology transfer efficiency measure system

| Input index | Personnel input | A1: The total time equivalent of R&D personnel (person/year) |
|---|---|---|
| | Capital investment | A2: Internal expenditure of R&D funds (RMB) |
| | | A3: Expenditure on new product development (10,000 yuan) |
| Output indicator | Patent output | A4: Effective invention patent number (piece) |
| | Economic output | A5: Exports of high-tech products ($10,000) |
| | | A6: Sales of new products (10,000 yuan) |

### III. B.  Data sources

The lag between R&D inputs and outputs is more appropriate to take the average of 4 years, so this paper takes the average of 4 years of R&D funding and personnel inputs in 2021-2023, and the data are all from the Annual Statistical Data on Science and Technology in China in that year, and the technology transfer realized through the technology market, the execution rate of its contract in the current year is more than 70% and most of them can be executed in 3 years, so this paper takes the The 3-year average of the turnover of absorbed technology contracts in 2022-2023, the data are all from the Annual Data of China Technology Market Statistics of that year, the amount of actual utilization of foreign capital in each province and region of China is compiled from the information released by the network of each province and region, the output technology contract turnover is derived from the Annual Data of China Technology Market Statistics of 2023, the data of patents, GDP The output technology contract turnover is from the 2023 China Technology Market Statistical Annual Report, and the patent and GDP data are from the 2024 China Statistical Yearbook.

## IV.  Empirical analysis

### IV. A.  Efficiency measures

Using DEPA2.1 software, substituting the input-output data of technology transfer in Chinese provinces and regions into the BCC model, and calculating the model based on the output-oriented perspective, we get the evaluation results of technology transfer efficiency in 30 provinces and regions as shown in Table 2. There is still room for improvement in the comprehensive efficiency of technology transfer in 30 provinces and regions in China, with an average of 0.876. The comprehensive efficiency of technology transfer in 12 of these provinces and regions reaches DEA efficiency, i.e., the technology transfer in these provinces and regions reaches both technology efficiency and scale efficiency, which are Beijing, Jiangsu, Zhejiang, Anhui, Shandong, Guangxi, Guizhou, Shaanxi, Gansu, Qinghai, and Xinjiang, respectively. On the other hand, the technology transfer in other provinces and regions shows non-DEA effective, especially the comprehensive efficiency of technology transfer in Tianjin, Shanxi, Liaoning, Jilin, Hubei, and Ningxia is less than 70%, which to a certain extent reflects that these provinces and regions have more room for improvement in the allocation of scientific and technological resources, technology transfer incentives and other scientific and technological policy formulation and implementation.

In the DEA method, the comprehensive efficiency is also known as scale technical efficiency, which is essentially the product of technical efficiency and scale efficiency. Observing Table 2, it is not difficult to find that the main

reason leading to the non-DEA-effective comprehensive efficiency of technology transfer in some provinces and regions is that their scale efficiency is non-DEA-effective, i.e., scale ineffective.

Table 2: DEA values of each decision-making unit

| DMU | Integrated efficiency | Technical efficiency | Scale efficiency |
|---|---|---|---|
| Beijing | 1 | 1 | 1 |
| Tianjin | 0.659 | 0.726 | 0.943 |
| Hebei | 0.919 | 0.993 | 0.917 |
| Shanxi | 0.626 | 0.948 | 0.685 |
| Inner Mongolia | 0.9 | 1 | 0.9 |
| Liaoning | 0.681 | 0.753 | 0.904 |
| Jilin | 0.648 | 0.721 | 0.897 |
| Heilongjiang | 0.834 | 0.895 | 0.941 |
| Shanghai | 0.869 | 0.916 | 0.973 |
| Jiangsu | 1 | 1 | 1 |
| Zhejiang | 1 | 1 | 1 |
| Anhui | 1 | 1 | 1 |
| Fujian | 0.809 | 0.871 | 0.925 |
| Jiangxi | 0.931 | 0.953 | 0.996 |
| Shandong | 1 | 1 | 1 |
| Henan | 0.927 | 1 | 0.943 |
| Hubei | 0.689 | 0.789 | 0.866 |
| Hunan | 0.847 | 0.876 | 0.965 |
| Guangdong | 0.832 | 0.984 | 0.817 |
| Guangxi | 1 | 1 | 1 |
| Hainan | 1 | 1 | 1 |
| Chongqing | 0.912 | 0.959 | 0.981 |
| Sichuan | 0.743 | 0.792 | 0.946 |
| Guizhou | 1 | 1 | 1 |
| Yunnan | 0.852 | 0.964 | 0.923 |
| Shaanxi | 1 | 1 | 1 |
| Gansu | 1 | 1 | 1 |
| Qinghai | 1 | 1 | 1 |
| Ningxia | 0.651 | 1 | 0.657 |
| Xinjiang | 1 | 1 | 1 |

Further categorizing the provinces and regions according to the size of their comprehensive efficiency of technology transfer, the comprehensive efficiency evaluation of each decision-making unit is shown in Table 3. The provinces and regions with a comprehensive efficiency of technology transfer of 1, i.e., effective DEA, account for 40% of the total number of 30 provinces and regions in China. Since the technology market has become an important way to realize technology transfer, from the perspective of the technology market, five provinces and regions among these 12 provinces and regions, Beijing, Jiangsu, Anhui, Shaanxi and Gansu, fully show their ability to export technology, i.e., scientific and technological services, in regional technology transfer. On the other hand, seven provinces and regions, namely Zhejiang, Shandong, Guangxi, Hainan, Guizhou, Qinghai and Xinjiang, have mainly demonstrated their ability to absorb technology, i.e., these provinces and regions have actively and fully absorbed and utilized the scientific and technological resources of other provinces and regions to develop their own science and technology and economy through technology transfer. A total of 11 provinces and regions, accounting for 36.7%, have a combined efficiency of technology transfer above 0.8, of which Heilongjiang, Shanghai, Jiangxi, Guangdong and Chongqing have more technology output than technology absorption, while Hebei, Inner Mongolia, Fujian, Henan, Hunan and Yunnan mainly absorb technology in technology transfer. The total number of provinces and regions with average overall efficiency of technology transfer is seven, i.e., about one-fifth of China's provinces and regions have an efficiency of technology transfer lower than 0.8, and there is much room for improvement.

Table 3: Comprehensive efficiency evaluation of each decision-making unit

| Regional technology transfer efficiency | 1 | 0.8-1 | <0.8 |
|---|---|---|---|
| Evaluation | Good | Better | General |
| Number of provinces and cities | 12 | 11 | 7 |
| Accumulated | 12 | 22 | 30 |
| Proportion (%) | 40 | 36.7 | 23.3 |
| Accumulated | 40 | 73.3 | 100 |

## IV. B.  Analysis of technical efficiency and scale efficiency

According to the model calculation results, combined with the principle of determining the technical efficiency and scale efficiency of decision-making units, the results of technical efficiency and scale efficiency of technology transfer in each province and region are obtained as shown in Table 4. Technical efficiency is the maximum output that a decision-making unit can obtain under the condition of a given input combination. There are 16 out of 30 provinces and regions in China whose technical efficiency reaches DEA effective, accounting for 56.33% of the total. Further, combining with Table 2, it is not difficult to find that the comprehensive efficiency of technology transfer in 5 out of these 16 provinces and regions is non-DEA effective, including Hebei, Inner Mongolia, Ningxia, Henan, and Guangdong, which is due to the fact that their scale efficiency is not DEA effective.

Scale efficiency, also known as returns to scale, examines whether the provinces and regions carry out technology transfer activities at the most appropriate input scale under the condition of a certain level of technology. As can be seen from Table 4, among the 30 provinces and regions in China, 12 of them are provinces and regions with constant scale efficiency and synchronized changes with comprehensive efficiency, i.e., 40% of the provinces and regions have reached scale efficiency and are at the point of optimal return. Only Ningxia is in the stage of increasing scale efficiency, while the remaining 17 provinces and regions are in the stage of decreasing scale efficiency, i.e., these provinces and regions need to stabilize their existing scales and regulate the direction and quantity of inputs and outputs in order to realize the scale efficiency of DEA.

Table 4: Technical efficiency and scale efficiency of each decision-making unit

| Technical efficiency | Number of DUM | Proportion (%) | Scale efficiency | Number of DUM | Proportion (%) |
|---|---|---|---|---|---|
| Dea validity | 18 | 60 | Invariant | 12 | 40 |
| Non-dea effective | 12 | 40 | Increasing | 1 | 3.33 |
| Tot | 30 | 100 | Diminishing | 17 | 56.67 |

## IV. C.  Malmquist index efficiency change measures

The Malmquist index and the changes of each efficiency of technology transfer in China from 2018 to 2024 are shown in Table 5. The results show that:

First, in recent years, the efficiency of technology transfer in China has generally shown a downward trend, and the optimal frontier of technology transfer has declined, and from the mean value, the average efficiency index of technology transfer in China is 0.96, and the index of technological progress and the index of technological efficiency are 0.966 and 0.988, respectively, and the gap between the capacity of technology transfer in each province and region and the frontier has increased, and the decline in the average efficiency of technology transfer is mainly subject to technological progress constraints. From the decomposition index of technical efficiency, the technical efficiency index is mainly driven by pure technical efficiency, in which the average pure technical efficiency index is 1.026, indicating that the resource allocation of input factors for technology transfer has been improved, and the average scale efficiency index is 0.985, and in the long run, China's technology transfer tends to deviate from the optimal production scale.

Secondly, in terms of the dynamic evolution of technology transfer efficiency, the Malmquist index shows a fluctuating process of increasing and then decreasing, and the Malmquist index of technology transfer efficiency reaches a maximum value of 1.648 from 2020 to 2021. From the perspective of decomposition indicators, the technical progress index and Malmquist index have similar trends, also showing the characteristics of rising and then declining, while technical efficiency, pure technical efficiency and scale efficiency have the same trend. It is worth noting that during the evaluation period, only the Malmquist index, technological progress index, technological efficiency index, pure technological efficiency index, and scale efficiency index are all greater than 1 in the period from 2020 to 2021, which corresponds to the process of China's technology transfer development, i.e., on the basis of the large-scale development of the technology market system, the operation of the China Technology Transaction Information Service Platform (CTISP) will enable the initial formation of a new demand-oriented cross-regional

technology transfer system supported by informationization by 2020. This corresponds to the development process of technology transfer in China, that is, on the basis of the large-scale construction of technology market system, the operation of China Technology Transaction Information Service Platform in 2020 will make the demand-oriented, informationization-supported trans-regional new technology transfer system initially take shape, so 2020 is selected as an important time point. Considering the efficiency is the position of the productivity of different decision-making units relative to the production boundary, the productivity of multiple decision-making units at the same point in time can form a production boundary under the condition of technological variability. The traditional DEA model assumes that all decision-making units have the same level of technology (only the technical efficiency is different), which is only suitable for efficiency evaluation of cross-sectional data. Therefore, the values of technology transfer efficiency at the starting and ending time points of the evaluation period (2018 and 202), and at the important time point (2020) will be calculated by province and region, so as to analyze the changes in China's technology transfer efficiency, instead of calculating the technology transfer efficiency across multiple years.

Table 5: The Malmquist index and various efficiency changes of technology transfer

| Evaluation period | Malmquist | Technological progress | Exponential efficiency | Index pure technical efficiency | Index scale efficiency index |
|---|---|---|---|---|---|
| 2018~2019 | 0.63 | 0.669 | 0.941 | 1.042 | 0.9 |
| 2019~2020 | 0.958 | 1.14 | 0.84 | 0.94 | 0.89 |
| 2020~2021 | 1.648 | 1.104 | 1.51 | 1.214 | 1.239 |
| 2021~2022 | 0.753 | 0.918 | 0.795 | 0.892 | 0.893 |
| 2022~2023 | 1.083 | 1.074 | 0.997 | 0.97 | 1.017 |
| 2023~2024 | 0.936 | 0.943 | 1.018 | 1.039 | 0.967 |
| Mean | 0.96 | 0.966 | 0.988 | 1.026 | 0.985 |

# V.   Analysis of Influencing Factors of Technology Transfer and Improvement Strategies of Innovation Paths

This chapter analyzes the factors affecting technology transfer based on RF-Tobit to provide objectives and programs for the improvement of the efficiency of technology transfer in provinces and districts.

## V. A.   Influence factor analysis based on RF regression

RF is used for regression analysis, directly using the RF algorithm to fit the functional relationship, the value of the technology transfer efficiency as the dependent variable, the influence factors as independent variables, the use of the "randome Forest package" in the R language to complete the random forest based on the establishment of the efficiency of the factors of the regression tree model [19], the use of multiple classification trees to classify the data, by selecting the independent variables caused by the amount of change in the appraisal criteria, the relative influence of the selected independent variables on the technology transfer efficiency to give the importance of each independent variable score. Using multiple classification trees to categorize the data, the relative influence of the selected independent variables on the efficiency of technology transfer is derived by selecting the amount of change in the identification criteria caused by each independent variable, and the importance of each independent variable is rated.

RF regression was utilized to rank the impact of each influence on the efficiency value, which was measured using both the mean accuracy decline and the Gini index. Mean square error is equivalent to mean accuracy decrease and indicates the relative importance, that is, for each variable randomly assigned, an increase in error is equivalent to a decrease in accuracy, so the more important the factor the greater the mean square error, the value indicates the contribution to the accuracy of the prediction of the target variable. Nodal purity (based on the Gini index), the mean value of the change in the Gini index is used as a measure of the importance of the variable.

The random forest regression of technology transfer efficiency with the influencing factors is shown in Figure 1. The variable importance was assessed using both decreasing mean square error and decreasing impurity, and some gaps were obtained in the variable importance. Combining the two results, in order of importance, the first and foremost of the influencing factors is economic output, which is represented in this paper by the export value of high-tech products (A5) and the sales revenue of new products (A6), which have a greater impact on the efficiency of technology transfer. The lowest ranking is internal expenditure of R&D funds (A2), indicating that the internal expenditure of funds at the time of R&D has the least influence on the efficiency of technology transfer.
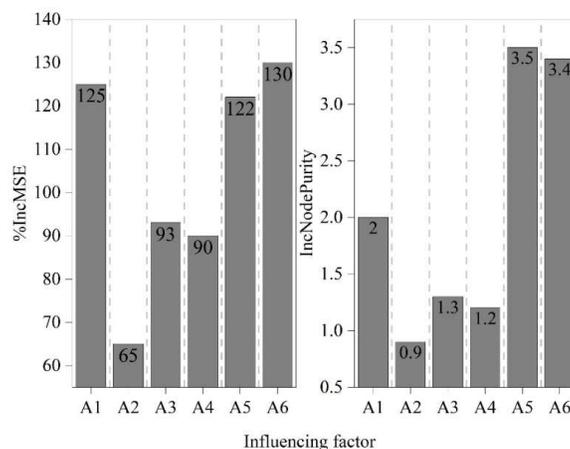
Figure 1: RF Regression of Technology Transfer Efficiency and Influencing Factors

## V. B. Influence factor analysis based on Tobit regression

The value of technology transfer efficiency as an independent variable and the influencing factors as a dependent variable were used to perform Tobit regression and GMM test using Stata software, and the analyzed data are shown in Tables 6 and 7, respectively.Tobit is based on the principle of maximum likelihood estimation to regress the influencing factor variables [20], and in order to ensure that the estimation results are robust, systematic GMM estimation was used for the assessment of the test, which does not need to satisfy certain assumptions and is more realistic than other parametric methods.

Tobit is based on the principle of maximum likelihood estimation to regress the influencing factor variables, and in order to ensure the robustness of the estimation results, the system GMM estimation method is used to reassess the test, which does not need to satisfy certain assumptions and is more realistic than other parametric methods. Taking the value of technical efficiency as the dependent variable and the six influencing factors such as full-time equivalent of R&D personnel, internal expenditure of R&D funds, expenditure of new product development funds, number of effective invention patents, export amount of high-tech products and sales revenue of new products as the independent variables, the regression effect is significant as a whole. From the Tobit regression results, the expenditure on new product development (A3) is significant at the 10% significance level. New product sales revenue (A6) is significant at 1% significance level, while all other variables are insignificant.GMM test results and Tobit regression have some differences, in the test results, high-tech product exports (A5) is significant, and the expenditure on new product development (A3) is insignificant.

Table 6: Tobit Model Regression

| Efficiency | Coef. | Std.Err. | T | P>|T| | [95%Conf.Interval] | |
|---|---|---|---|---|---|---|
| A1 | -0.007 | 0.001 | 0.313 | 0.742 | -0.002 | -9.9749E-4 |
| A2 | 0.00349 | -0.01231 | 0.865 | 0.396 | 0.01116 | -0.01219 |
| A3 | -0.04462* | 0.0445 | -1.767 | 0.082 | -0.13768 | -5.649E-4 |
| A4 | 0.00122 | -0.0163 | -1.111 | 0.274 | -0.02717 | -0.00239 |
| A5 | -0.01656 | 0.00712 | -1.055 | 0.291 | -0.04253 | 0.02541 |
| A6 | -0.03462*** | 0.01492 | -2.653 | 0.011 | -0.0532 | -0.01104 |
| _cons | 1.12621 | 0.84382 | 1.34 | 0.185 | -0.49948 | 2.73589 |

Table 7: Factors Affecting Efficiency GMM Test

| Efficiency | Coef. | Std.Err. | T | P>|T| | [95%Conf.Interval] | |
|---|---|---|---|---|---|---|
| A1 | 0.028 | -0.011 | -0.76 | 0.449 | 0.002 | -0.004 |
| A2 | 0.0036 | -0.00972 | 1.243 | 0.211 | 0.00408 | 0.00511 |
| A3 | -0.02909 | 0.00714 | -1.448 | 0.159 | -0.05265 | 0.02347 |
| A4 | -0.00656 | -0.00557 | -1.301 | 0.207 | -0.01039 | 0.01828 |
| A5 | -0.00874* | -0.00255 | -1.816 | 0.079 | -0.03637 | -0.00311 |
| A6 | -0.0184*** | 0.02038 | -3.199 | -0.014 | -0.03692 | -0.01689 |
| _cons | 1.66036 | 0.55902 | 3.032 | -0.003 | 0.58518 | 2.73655 |

Tobit regression results and RF regression results have some differences, in the RF results the factor is ranked higher, but in the Tobit panel regression failed to pass the test of significance, combined with the results of the two, the Tobit regression results as the main, RF results as a reference to the impact of the factors of a comprehensive analysis.

### V. C.   Strategies for improving innovation pathways for technology transfer

Analyzing the efficiency of technology transfer in 30 provinces, cities and autonomous regions through DEA-Malmquist method, and exploring the influencing factors of their efficiency through two regression methods of RF and Tobit respectively, this paper puts forward the following suggestions:

(1) Encourage the development of collaborative innovation among regions. At present, the development of technology transfer in various regions is relatively unbalanced, and provinces and cities need to actively promote the development of inter-regional collaborative innovation and establish a cooperation mechanism, so as to narrow the gap, take advantage of the strengths and complement the shortcomings of the region to improve regional capacity for independent innovation, and to implement differentiated measures according to the local conditions and establish a networked pattern of collaborative development and innovation drive [21].

(2) Adjustment of industrial structure. Promote the reform of enterprises in the secondary and tertiary industries, utilize modern new technologies for the transformation, transformation and upgrading of traditional industries, and promote the rapid development of the science and technology service industry. Adjust the structure of foreign trade, develop independent intellectual property rights, reduce the degree of dependence on foreign markets, enhance the competitiveness of local products, so that foreign trade effectively pull the local economic growth.

(3) Rationalize the allocation of R&D resources: R&D funds and personnel are the core innovation resources, improve the construction and configuration of the technology market, appropriately adjust the support of enterprises and the government, regulate the structure of inputs and outputs, make the use of funds open and transparent, reduce the redundancy of funds, and increase the supervision to prevent the waste of resources. Optimize the talent management mechanism, deepen the reform of the appraisal system, and fully mobilize the enthusiasm of scientific researchers.

## VI.   Conclusion

Measured by data envelopment analysis and Malmquist index, the technology transfer efficiency of 30 provinces and regions in China shows obvious differences, and the average comprehensive efficiency is 0.876, indicating that China's technology transfer efficiency still has more room for improvement. Twelve provinces and regions such as Beijing, Jiangsu, Zhejiang and other provinces and regions have reached DEA effective technology transfer efficiency, while seven provinces and regions such as Tianjin, Shanxi and other provinces and regions have a technology transfer efficiency lower than 0.8. From a dynamic point of view, the Malmquist index of China's technology transfer in 2018-2024 is 0.96, the index of technological progress is 0.966, and the index of pure technological efficiency is 1.026, which suggests that the decline in the efficiency of technology transfer is mainly constrained by technological progress rather than resource allocation problems. The analysis of influencing factors shows that the sales revenue of new products is significant at the 1% significance level, and the export amount of high-tech products is outstanding in RF regression, which has an important influence on technology transfer efficiency.

For different efficiency provinces and regions, inter-regional cooperation and innovation should be strengthened and technology transfer networks should be built; for inefficient provinces and regions, industrial structure should be optimized and reform of secondary and tertiary industry enterprises should be strengthened; for provinces and regions with disproportionate input-output ratio, R&D resources should be reasonably allocated, talent management mechanism should be improved, and use of funds should be made more efficient. Multiple measures to enhance the efficiency of regional technology transfer will promote the establishment of a more dynamic regional innovation system in China.

## Funding

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