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ANALYSIS OF INNOVATION EFFICIENCY AND INFLUENCING FACTORS OF LISTED COMPANIES IN BEIJING-TIANJIN-HEBEI ECONOMIC ZONE BASED ON IMPROVED DEA

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Abstract. This study investigates the innovation efficiency of listed companies in the Beijing-Tianjin-Hebei region from 2015 to 2021. Various models are applied to analyze the data and identify factors affecting innovation efficiency. The findings show that, after adjusting the data, most listed companies' scale efficiency decreases significantly. Pure technical efficiency also decreases, but not to a substantial degree. These changes lead to an overestimation of innovation efficiency. The analysis reveals that the business environment influences the innovation index of listed companies. Additionally, there is a positive relationship between enterprise nature, equity concentration, urban financial expenditure, and innovation efficiency. Longer-established companies face challenges in improving their innovation efficiency. Most companies demonstrate improvements in technical efficiency, indicating relatively high levels of technical efficiency. However, continuous technological progress is crucial. The paper suggests that policymakers and company management should prioritize the enterprise's nature, equity concentration, and urban financial expenditure to cultivate innovation efficiency.

Keywords: Innovation Efficiency; DEA-BBC Model; Tobit Model; Malmquist Index

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JEL Classifications: C61, C24, O47, O31

Additional disciplines: Regional development, business management, innovation management, economic growth

1. Introduction

The Beijing-Tianjin-Hebei Economic Zone holds significant prominence as one of China's major planned economic zones. Widely regarded as the potential "third pole" of Chinese economic growth, it stands out due to the dense concentration of cities and its robust, comprehensive strength within China. Moreover, the region is pivotal in the national coastal economic layout, alongside the Yangtze River Delta and the Pearl River Delta.

This region harbours a wealth of innovative resources, which provide invaluable support for local listed and developing companies in their pursuit of innovation-driven growth. Capitalizing on its favourable policies, strategic location, and abundant human resources, Beijing has prioritized the establishment of a digital economic innovation ecosystem, transforming it into a hub for digital economic innovation resources across the country. Consequently, Beijing stands as a highland for the digital industrialization of China, acting as a catalyst for industry digitization initiatives and boasting abundant innovation resources. Meanwhile, Hebei and Tianjin

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benefit from their geographical advantages, leveraging the abundant innovation resources of Beijing to drive their innovation-oriented development.

To improve their competitiveness, product quality, and progress, companies rely heavily on innovation. The effectiveness of innovation directly impacts a company's ability to adapt and the frequency of product updates. For companies that are publicly listed, technological innovation is the source that ensures their survival and growth. It is widely recognized that innovation is crucial for companies to thrive in a fiercely competitive market.

This paper aims to investigate innovation efficiency in listed companies in the Beijing-Tianjin-Hebei region and identify influencing factors. The study contributes to the rational utilization of resources, enhances innovation efficiency and competitiveness, aids in effective development planning, and boosts market value. The findings reveal that adjusting data leads to decreased scale efficiency and a lesser decline in pure technical efficiency, resulting in overestimating innovation efficiency. The analysis emphasizes the impact of the business environment on the innovation index. In addition, a positive relationship exists between enterprise nature, equity concentration, urban financial expenditure, and innovation efficiency. Longer-established companies face challenges in improving innovation efficiency, while most companies demonstrate improved technical efficiency. Continuous technological progress is crucial. Hence, policymakers and company management should prioritize enterprise nature, equity concentration, and urban financial expenditure to cultivate innovation efficiency.

2. Literature review

After thoroughly reviewing the existing literature, it becomes evident that innovation efficiency has garnered significant attention from experts and researchers both domestically and internationally. Innovation efficiency refers to the ability to maximize innovation output given a set of inputs and effectively measure innovation capability (Saunila & Ukko, 2012). Two primary methods are commonly employed for measuring innovation efficiency: parametric and non-parametric methods. The parametric method is exemplified by Stochastic Frontier Analysis (SFA), which offers advantages such as differentiating the error term, hypothesis testing of results, and measuring absolute efficiency. On the other hand, the non-parametric method is exemplified by Data Envelopment Analysis (DEA), which eliminates the need for specific functional forms, avoids subjectivity-related errors, and provides insights into the adjustment direction and range of non-efficient inputs and outputs.

DEA is a frequently used method for measuring the innovation efficiency of enterprises. It is a non-parametric frontier model based on mathematical programming (Charnes et al. 1978; Banker and Cooper 1984; Walton et al., 2019). DEA has become a preferred tool for studying the efficiency of production systems with multiple inputs and outputs. As an effective non-parametric method, DEA analyzes and estimates the production technology frontier and the relative efficiency of benchmark technology by examining input and output data. When evaluating innovation efficiency, researchers have not only employed the traditional DEA model but have also proposed several improved models based on the traditional DEA model. Examples include the two-stage DEA, three-stage DEA model, DEA-R, and ultra-efficiency DEA, among others. The three-stage DEA model calculates the true efficiency of decision units operating under the same external environment and random interference, providing a more comprehensive reflection of innovation efficiency under multiple factors.

From a scale perspective, researchers have primarily explored innovation efficiency at the regional scale, the scale of multi-type enterprises, the scale of single-type enterprises, and the institutional scale (Jingqiang, 2011; Fan et al., 2019; Munodawafa & Johl, 2019; Du et al., 2022). At the enterprise level, researchers predominantly utilize the two-stage data envelopment analysis model and the three-stage data envelopment analysis model to explore enterprise innovation efficiency (Fu et al., 2022; Fang et al., 2020; Erdin & Çağlar, 2022; Teirlinck & Khoshnevis, 2022). Additionally, researchers have employed models such as the two-stage network data envelopment analysis model, dynamic two-stage network data envelopment analysis model, three-stage ultra-

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efficiency data envelopment analysis model, DEA-Malmquist Index analysis method, DDF model combined with Malmquist Index, SBM-DEA model based on ultra-efficiency relaxation, and others (Edquist et al., 2018; Šūmakaris et al., 2021; Ye et al., 2021; Santos et al., 2020; Long et al., 2020; Bakhtiar et al., 2021; Pan et al., 2021). From a regional perspective, researchers have primarily explored innovation efficiency at the national level, provincial and municipal levels, and economic zone level (Kalmakova et al., 2021; Trianni et al., 2013; Shin et al., 2018; Xu et al., 2020; Nan, 2021; Janger et al., 2017; Lai et al., 2020). At the national level, researchers have utilized models such as the two-stage network envelopment analysis model, DEA-Bootstrap and Malmquist Index model, DEA-SBM model, DEA-EATWIOS model, and dynamic data envelopment analysis to explore innovation efficiency (Kalmakova et al., 2021; Trianni et al., 2013; Shin et al., 2018; Xu et al., 2020; Nan, 2021). At the provincial and municipal levels, researchers primarily employ the two-stage data envelopment analysis model, DEA-SBM model and GML indices, measurement direction distance function model based on relaxation, ideal window width data envelopment analysis window model, non-parametric data envelopment analysis and direction distance function (DEA-DFF) model, and other methods (Janger et al., 2017; Lai et al., 2020; Li et al., 2018; Cheng et al., 2022). At the economic zone level, researchers have mainly used models such as the super-slack-based metric and the global Malmquist-Renberg Index (Vergera et al., 2021).

From the perspective of innovation efficiency research, researchers have primarily explored various dimensions of innovation efficiency, including general innovation efficiency, green innovation efficiency, ecological innovation efficiency, technological innovation efficiency, and green technology innovation efficiency (Ledeneva, 2020; Goddard, 2020; Yeo et al., 2015; Li et al., 2017; Wang & Mu, 2019). However, several shortcomings still exist in the existing studies on innovation efficiency. Firstly, in terms of research scale, most researchers have focused on either the national scale or specific types of enterprises or departments, with limited research conducted on enterprise innovation efficiency within specific regions (Krejčí & Šebestová, 2019). This approach poses challenges in processing and measuring samples with a unified standard due to significant differences between different enterprises. Consequently, there is a need for more research on enterprise innovation efficiency within specific regions. Secondly, regarding research methods, most researchers have utilized a single DEA model to examine enterprise innovation efficiency. These models include the traditional DEA model, two-stage DEA model, and three-stage DEA model, among others (Mustafid, 2013; Li et al., 2014; Li & He, 2017). However, there is a lack of studies that combine the DEA model with other methods such as the Malmquist Index or Tobit regression model to explore innovation efficiency.

Innovation efficiency is an area of interest among experts and researchers. DEA and SFA are commonly used methods for measuring innovation efficiency, with DEA being a frequently used non-parametric method. Researchers have studied innovation efficiency at different scales, including enterprise, regional, and national levels. However, existing studies still have limitations, such as limited research on enterprise innovation efficiency within specific regions and a lack of studies combining DEA with other methods. Future research should address these gaps to enhance our understanding of innovation efficiency.

The aim of this paper is to address these gaps by examining innovation efficiency and its determinants in listed companies in the Beijing-Tianjin-Hebei region. We use the DEA-BCC model and the Malmquist Index method for this purpose. The results of this study are expected to provide valuable insights and recommendations for the future growth of innovation in listed companies in the Beijing-Tianjin-Hebei region.

3. Sample and Research Methodology

This study focuses on examining innovation efficiency and its influencing factors among listed companies in the Beijing-Tianjin-Hebei region. The research sample consists of 563 selected companies. To ensure the reliability of the analysis, several treatments were applied to the sample. Firstly, companies with missing data on key variables such as the number of R&D personnel, R&D investment amount, and number of patent authorizations were excluded, resulting in the removal of 142 companies. Secondly, companies that went public after 2015 were excluded, leading to the elimination of 198 companies. Additionally, one "special treatment" company was excluded from the sample, which is classified by China securities regulator to be "unsafe investment". To ensure the compatibility of the data with the DEAP software (version 2.1), efforts were made to exclude companies with negative input-output data. For cases where negative values could not be excluded, they were replaced with a small positive value, specifically 0.0001. This process resulted in the elimination of 81 companies. After these treatments, a final sample of 63 companies was obtained, with 36 located in Beijing, 13 in Tianjin, and 14 in Hebei. The innovation efficiency of these 63 companies was evaluated using the DEA-BCC model, Tobit Model, and Malmquist Index. The study also examined the influencing factors of innovation efficiency to provide recommendations for enhancing the innovation efficiency of listed companies in the Beijing-Tianjin-Hebei region.

DEA-BCC Model

In this study, we adopted the BCC model proposed by Banker et al. (1984), which is an input-oriented model with variable scale returns to scale (VRS). The formula for the input-oriented DEA-BBC Model is as follows:

$$\min[\theta\text{-}\varepsilon(\sum_{i=1}^{n} s_i^- + \sum_{r=1}^{s} s_r^+)]$$

$$\text{s.t.} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta\, x_{ij0}, i \in (1,2, \ldots, m)$$

$$\sum_{j=1}^{n} Y_{rj}\lambda_j - s_r^+ = \theta\, y_{rj0}, r \in (1,2, \ldots, s)$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\theta \geq 0$$

$$s_i^-, s_r^+ \geq 0, i \in (1,2, \ldots, m), r \in (1,2, \ldots, s)$$

$$\lambda_j \geq 0, \ j=1,2,\ldots,n$$

In the formula, m represents the number of input variables, s represents the number of output variables, θ represents the effective value of the decision unit DMU, that is, the pure technical efficiency of the decision unit DMU; x_{ij} represents the i-th input factor of the j-th decision unit; y_{rj} represents the r-th output factor of the j-th decision unit; λ represents the linear combination vector of n DMUs; s^- and s^+ represent input and output slack variables, respectively; ε represents non-Archimedes infinitesimal quantity, usually taken as 10^{-6}. If θ=1, $S^+=1$ and $S^-=0$, the decision unit is DEA strongly efficient, and the decision unit achieves the best combination and maximum output; If θ=1 and $S^+\neq 0$ or $S^-\neq 0$, the DMU of weak DEA is efficient; if θ>1, the DMU is not DEA efficient, indicating that there is certain efficiency improvement space for the DMU. In this case, the closer θ is to 1, the closer the efficiency is to being effective.

DEA-Malmquist Index

The Malmquist Index is a widely employed measure for assessing changes in total factor productivity (TFP), thereby rendering it appropriate for the examination of innovation efficiency and the determinants thereof among publicly traded firms in the Beijing-Tianjin-Hebei region. The Malmquist Index was originally devised by Caves et al. (1982), and subsequently, Färe et al. (1994) formulated a model employing a distance function to represent it.

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This model employs directional output and directional input to delineate the distance function, and the distance function D for the output variable can be mathematically represented as equation (1).

$$D_0(x,y) = \inf\{\delta:(x,y/\delta) \in p(x)\} \qquad (1)$$

In equation (1), x and y represent the input vector and output vector, respectively. P (x) represents the possible set of innovation efficiency, δ is a representative quantity of directional output efficiency indicators. The relationships in the following table can be obtained through nonlinear operations:

Relationship between y and p (x)	function value
Y is outside the set p (x)	Greater than 1
Y at the boundary of set p (x)	Equal to 1
Y is within the set p (x)	Less than 1

The innovation efficiency of companies listed in the Beijing-Tianjin-Hebei region is subject to the influence of various external factors. In order to ascertain the reasonable factors that impact innovation efficiency, the Malmquist Index, renowned for its capability to effectively deal with multi-input and multi-output datasets, is employed.

Assuming (x^t, y^t) is the input and output of period t, and (x^{t+1}, y^{t+1}) is the input and output of period t+1, then D_0^t and D_0^{t+1} represent the distance functions of the t period and the t+1 period, respectively. The Malmquist total factor productivity of output can be represented by equations (2) and (3).

$$M_t(x^t,y^t,x^{t+1},y^{t+1}) = \frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)} \qquad (2)$$

$$M_{t+1}(x^t,y^t,x^{t+1},y^{t+1}) = \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)} \qquad (3)$$

M_t is the total factor production index, which means that under the technical T reference of period t, if M<1, it indicates that the total factor productivity of the decision-making unit has decreased compared to the previous period. If M>1, it indicates that the efficiency level of the decision-making unit has improved.

Färe et al. (1994) believes that the indexes of the two periods are stacked in economic sense. Because the randomness of period selection may cause different analysis results, the geometric mean of multiple periods can be used to measure total factor productivity, that is

$$\begin{aligned} M_0(x^t,y^t,x^{t+1},y^{t+1}) &= (M_t \times M_{t+1})^{\frac{1}{2}} \\ &= \left\{\left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}\right]\left[\frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)}\right]\right\}^{\frac{1}{2}} \\ &= \left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}\right] \times \left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})} \times \frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}} \end{aligned} \qquad (4)$$

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Among them, the Malmquist Index can decompose the technical efficiency change index Effch and the technical progress index Tech when the return to scale is unchanged, that is, the above equation can be written as this equation:

$$M_0(x^t, y^t, x^{t+1}, y^{t+1}) = (M_t \times M_{t+1})^{\frac{1}{2}} = \text{Effch} \times \text{Tech} \quad (5)$$

Among them:

$$\text{Effch} = \frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)}$$

$$\text{Tech} = \left[\frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)}\right]^{\frac{1}{2}}$$

When there is variability in the returns to scale, the index Effch, which represents the change in technical efficiency, can be further broken down into two components: the pure technical efficiency index "pech" and the scale efficiency index "sech". This decomposition is expressed through equation (6).

$$\text{Effch} = \text{pech} \times \text{sech} \quad (6)$$

Where: then D_v^t and D_v^{t+1} represent the distance function of period t and period t+1 under the condition of variable returns to scale.

$$\text{pech} = \frac{D_v^{t+1}(x_{t+1}, y_{t+1})}{D_v^{t+1}(x_t, y_t)}$$

$$\text{sech} = \left[\frac{D_v^{t+1}(x^{t+1}, y^{t+1}) / D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t) / D_v^t(x^t, y^t)} \times \frac{D_v^{t+1}(x^{t+1}, y^{t+1}) / D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t) / D_v^t(x^t, y^t)}\right]^{\frac{1}{2}} \quad (7)$$

Tobit Model

To explore the efficiency of innovation and the factors that affect it in the Beijing-Tianjin-Hebei region, we utilize the Tobit regression model and employ maximum likelihood estimation. The evaluation of innovation efficiency is conducted through the application of the standard Tobit regression model, which is defined by equation (7).

$$y_i = \begin{cases} 1 & Y_i^* > 1 \\ Y_i^* & 1 > Y_i^* > 0 \\ 0 & 0 > Y_i^* \end{cases} \qquad Y_i^* = \Sigma \beta x_i + \varepsilon_i \ (i = 1, 2, \ldots, \ n) \quad (8)$$

Among them, Y_i^* is the latent variable, y_i is the observable variable, X_i is the independent variable vector, ε_i represents the interference term, which is independent. It has a value range of N (0, σ), and follows normal distribution. β is the parameter to be estimated (eqution 8).

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Indicator System

The indicator system employed in this study encompasses three primary facets: input indicators, output indicators, and environmental indicators:

a. Input Indicators: The measurement and evaluation of innovation efficiency in listed companies within the Beijing-Tianjin-Hebei region is an intricate endeavour. Consequently, we have identified three pivotal indicators from the perspectives of human resources, financial resources, and physical resources. These indicators include the intensity of R&D personnel input, the intensity of R&D financial input, and enterprise assets, all of which serve as significant measures of the innovation index. R&D personnel input intensity is gauged by the number of R&D personnel present in the listed company, while R&D financial input intensity is ascertained through the R&D expenditure of the said company. Furthermore, enterprise assets are quantified by the total asset amount possessed by the listed company at the end of the given period.

b. Output Indicators: This research's focus lies on the innovation efficiency of listed companies in the Beijing-Tianjin-Hebei region. The output of innovation primarily encompasses knowledge and economic factors. In terms of knowledge output, we primarily assess the number of patents held by the listed company. On the other hand, for economic output, we evaluate the growth rate of operating profit and the company's primary business. Patents serve as technological mechanisms that incentivize innovation, with invention patents signifying the highest level. They not only reflect patent quality but also serve as a vital indicator of market value and R&D competitiveness. The growth rate of operating profit is determined by subtracting the disclosed total profit amount at the culmination of the given period from the disclosed total profit amount at the end of the previous period, and then dividing the result by the latter amount. Similarly, the growth rate of the core business is calculated by subtracting the disclosed core business income at the culmination of the given period from the disclosed core business income at the end of the previous period, and then dividing the result by the latter amount.

c. Environmental Indicators: In relation to environmental indicators, we primarily assess the following six dimensions:

   i. Duration of establishment. This possesses significant value attributes in enhancing the enterprise's capacity for absorbing knowledge. Simultaneously, the allocation of R&D funds fluctuates across various stages of the enterprise.
   ii. Enterprise nature. In China, enterprises can be primarily categorized into state-owned and non-state-owned, each exhibiting distinct levels of innovation efficiency.
   iii. Shareholder concentration within a company indicates a higher level of authority held by shareholders in terms of managing and supervising operations. This amplifies the likelihood of irrational decision-making due to excessive focus.
   iv. Degree of openness. Independent innovation and the expansion of openness are mutually reinforcing. The degree of openness plays a pivotal role in ameliorating the innovation efficiency of publicly listed companies. Concurrently, foreign investment and exchanges exert a stimulating effect on enterprise innovation.
   v. Economic development level. Varying levels of economic development across regions lead to differences in the attractiveness of talent and their impact on innovation efficiency. For enterprises, the economic development level of the market not only influences the strength of investment decisions pertaining to innovation but also affects innovation efficiency.
   vi. Government support. Government support in a specific field can effectively stimulate the innovative development of enterprises within that field. Consequently, this study employs local public budget expenditures as an indicator of government support within the region.

The indicator system and calculation methods used in this study are presented in Table 1.

Table 1. Indicator System

	Indicators	Units	Meanings
Input Indicators	R&D personnel input intensity	People	Number of R&D personnel of listed company
	R&D financial input intensity	Ten Thousand Yuan	R&D expenditure of enterprises
	Enterprise assets	Ten Thousand Yuan	Total assets of the enterprise at the end of the period
Output Indicators	Number of patents	Item	Number of patent authorizations of listed company
	Growth rate of operating profit	%	(Disclosed total profit amount at the end of the period minus disclosed total profit amount at the end of the previous period) / disclosed total profit amount at the end of the previous period
	Growth rate of the main business	%	(Disclosed main business income at the end of the period minus disclosed main business income at the end of the previous period) / disclosed main business income at the end of the previous period
Environmental Indicators	Years of establishment	Year	Duration of establishment time
	Enterprise nature	/	State-owned enterprises are recorded as 1, and non-state-owned enterprises are recorded as 0
	Shareholding concentration	%	The proportion of shares held by the largest shareholder
	Degree of openness	Ten Thousand USD	Foreign direct investment amount in the region
	Economic development level	Yuan	Per capita GDP in the region
	Government support	Yuan	Local general public budget expenditure

Analysis of Input-Output Correlation

In the process of using the DEA model for efficiency calculation, the selection of input and output indicators has a significant impact on the efficiency value results. We use the Pearson method to test whether the correlation between the composite indicators is significantly consistent with the monotonicity hypothesis, and the results are shown in Table 2. We can see that there is a significantly positive correlation between the input and output indicators, which meets the requirement of DEA model's consistency.

Table 2. Analysis of Input-Output Variable Correlation

	Number of R&D personnel	R&D investment amount (Yuan)	Total assets (Ten Thousand Yuan)
Number of patent authorizations	0.1935***	0.1405***	0.1626***
operating profit (Ten Thousand Yuan)	0.4618***	0.7061***	0.8710***
operating income (Ten Thousand Yuan)	0.6836***	0.9241***	0.9742***

*Note: ***、**、* indicate significance at the 1%, 5%, and 10% confidence level, respectively.*

4. Empirical Results

In this stage, we use Deap software (version 2.1) to analyze the innovation efficiency, pure technical efficiency, scale efficiency, and scale returns of 63 samples of listed companies in the Beijing-Tianjin-Hebei region, and the results are presented in Table 3, as well see Appendix.

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Table 3. Innovation Efficiency of 63 Listed Companies in the Beijing-Tianjin-Hebei Region in the First Stage

Stock code	Innovation Efficiency	Pure Technical Efficiency	Scale Efficiency	Scale Returns
000709	1	1	1	-
002049	0.942	0.943	0.999	drs
002271	1	1	1	-
002282	1	1	1	-
002350	1	1	1	-
300016	0.919	1	0.919	drs
300026	1	1	1	-
300075	0.352	0.385	0.916	irs
300107	0.365	0.388	0.943	irs
300119	0.405	0.421	0.962	irs
002579	0.494	0.506	0.976	irs
300137	0.58	0.587	0.987	irs
300138	0.503	0.52	0.967	drs
300229	0.55	1	0.55	drs
300255	1	1	1	-
300271	0.956	0.968	0.988	irs
300365	1	1	1	-
300371	1	1	1	-
300406	1	1	1	-
300407	1	1	1	-
300428	1	1	1	-
300455	1	1	1	-
300485	0.701	0.958	0.731	irs
300496	1	1	1	-
600008	0.754	0.862	0.875	irs
600095	0.587	0.753	0.78	irs
600056	0.861	0.901	0.955	irs
600062	0.658	0.701	0.938	irs
600135	0.901	0.969	0.93	irs
600161	0.888	0.908	0.978	irs
600195	0.884	0.899	0.983	irs
600206	0.833	0.842	0.99	irs
600271	0.835	0.858	0.973	irs
600329	0.773	0.806	0.959	irs
600409	0.8	0.811	0.987	irs
600429	0.544	0.938	0.58	irs
600468	0.616	1	0.616	irs
600480	0.571	1	0.571	irs
600535	0.58	0.926	0.627	irs
600560	0.619	0.886	0.699	irs
600582	0.355	0.571	0.622	irs
600583	0.357	0.525	0.68	irs
600717	0.659	0.68	0.969	irs
600803	0.645	0.648	0.995	irs
600855	0.551	0.555	0.992	irs
600874	0.677	0.68	0.994	irs
600900	0.707	0.709	0.996	irs
600980	0.766	0.768	0.998	irs
601088	0.794	0.795	0.999	irs
601117	0.414	0.583	0.71	irs
601186	0.478	0.574	0.832	irs
601390	0.467	0.506	0.923	irs
601633	0.499	0.538	0.929	irs
601668	0.481	0.514	0.936	irs
601669	0.434	0.48	0.905	irs

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601766	0.4	0.414	0.967	irs
601908	0.571	1	0.571	irs
601985	0.45	1	0.45	irs
603019	0.613	0.96	0.638	irs
603126	1	1	1	-
603698	1	1	1	-
603969	1	1	1	-
603979	0.495	0.733	0.675	irs

Annotation: "drs" represents decreasing scale returns, while "irs" represents increasing scale returns,

After conducting the necessary calculations, it has been determined that the average innovation efficiency of the 63 listed companies stands at 0.719. Furthermore, the average pure technical efficiency has been found to be 0.809, while the average scale efficiency is measured at 0.891. The proportion of increasing scale returns is observed to be the highest, followed by constant scale returns, whereas the proportion of decreasing scale returns remains the lowest. Based on the empirical findings from the initial stage, wherein environmental factors and random disturbances were not taken into consideration, it can be concluded that the innovation efficiency level of listed companies in the Beijing-Tianjin-Hebei region is moderate and requires further improvement. Additionally, the average scale efficiency of these companies surpasses their average pure technical efficiency. This suggests that enterprise scale factors hold a prominent position for listed companies in the Beijing-Tianjin-Hebei region, while enterprise technical factors assume a secondary role. These aforementioned results highlight the need for enhanced investment in innovation among listed companies in the Beijing-Tianjin-Hebei region and emphasize the importance of prioritizing the development of enterprise scale.

When not considering environmental factors and random disturbances, out of the 63 listed companies, 16 of them exhibit DEA efficiency. These companies, namely 002282, 002350, 300026, 300428, 000709, 002271, 300255, 300365, 300371, 300406, 300407, 300496, 300455, 603126, 603698, and 603969, are positioned at the forefront of innovation. Furthermore, these companies highlight innovation efficiency, pure technical efficiency, and scale efficiency, all at a value of 1. Additionally, their scale returns remain largely constant. Among these 16 companies, the highest number can be found in Beijing, followed by Hebei. Conversely, the lowest number of companies are situated in Tianjin. Moreover, it is worth mentioning that 24 enterprises exhibit an innovation efficiency below 0.6. Out of these, 16 companies are heavily influenced by pure technical efficiency factors, while 5 companies are significantly affected by scale efficiency. Extensive research has indicated that for companies with low innovation efficiency, pure technical efficiency takes on a dominant role in constraining innovation efficiency. Following this, the scale of the company plays a secondary role, with scale returns tending to increase.

The Second Stage: SFA Model Empirical Results

In the second stage of the DEA analysis, the SFA regression model was used for calculations. The dependent variables of the function were the number of R&D personnel, R&D investment amount, and total assets of the company. The explanatory variables were the year of company establishment, company nature, actual use of FDI in the city, per capita GDP of the city, and city financial expenditures. The results of the SFA regression estimation are shown in Table 4.

Table 4. SFA estimation results for the second stage

Parameters	Number of R&D personnel(redundancy)	R&D investment amount(redundancy)	Total assets
Constant term	21377.984***	8.461E+09***	5.780E+07***
Year of establishment	-691.353***	-2.920E+08***	-2.095E+06***
state-owned enterprise or non-state-owned enterprise	5145.275***	1.016E+09***	7.260E+06***
Shareholding ratio	171.141***	4.763E+07***	5.028E+05***
Per capita GDP of the city to which	-4.193E-03	1.711E+04	84.574***

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it belongs			
Financial expenditure of the city to which it belongs	1.188***	-1.751E+04***	545.868***
σ^2	1.140E+08***	3.107E+19***	1.678E+15***
Γ	0.976***	0.877***	0.961***
M	4418.628***	2.773E-09	3.492E-06
H	0.011***	-0.044***	-2.950E-02***
Log	-4156.558	-10214.883	-7845.988
LR	710.321	259.168	610.067

*Note: ***,**,* represent significant levels of 1%, 5%, and 10%, respectively. The value in parentheses is the T value. (T values greater than 2.58 are significant at the 1% level; 1.96-2.58 is significant at the 5% level; 1.64-1.96 is significant at the 10% level).*

The regression analysis presented in Table 4 reveals that the regression coefficient of the environmental variables holds significant value at the 1% level. This implies that the chosen indicators demonstrate rationality and have a close association with innovation efficiency. The γ values, which represent the number of R&D personnel and the total assets of the company within the regression model, are found to be very close to unity. This observation suggests that environmental variables have a substantial impact on innovation efficiency. Therefore, it is crucial to remove the environmental factors from the original dataset. It is worth noting that a positive regression coefficient in the table indicates that an increase in the explanatory variable effectively increases the redundancy of the dependent variable. On the other hand, a negative coefficient reduces the redundancy.

The regression coefficients related to the establishment year of a company show a significant negative influence on the number of R&D personnel, R&D investment amount, and total assets. This implies that the duration of a company's existence affects the growth of these three variables. As the company's establishment year increases, the number of R&D personnel, the amount of R&D investment, and total assets may become excessive, thus hindering the improvement of innovation efficiency.

The regression coefficients linked to the nature of the company, whether state-owned or non-state-owned, show a notable positive correlation with the number of R&D personnel, R&D investment amount, and total assets. The regression coefficients associated with the shareholding ratio of shareholders demonstrate a significant positive relationship with the number of R&D personnel, R&D investment amount, and total assets. This suggests that a concentrated shareholding structure can contribute to enhancing redundancy in terms of R&D personnel, R&D investment, and total assets. As a result, it can assist enterprises in effectively utilizing and planning their resources.

The regression coefficients related to per capita GDP do not play a significant role in determining the number of R&D personnel and R&D investment amount.

The regression coefficients associated with city financial expenditures reveal a significant positive correlation with the number of R&D personnel and total assets. Conversely, they display a significant negative relationship with the R&D investment amount.

The Third Stage: DEA Model Empirical Results after Adjustment

From the findings of the SFA regression model, it can be deduced that the efficiency of innovation is significantly influenced by both environmental and random factors. Consequently, to eliminate the impact of these factors, the treated samples were analyzed using Deap2.1. A comparison was then made between the processed data and the unprocessed data, as indicated in Table 4.

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Table 5. Innovation efficiency of 63 listed companies in Beijing-Tianjin-Hebei region in the first and third stages

Stock Code	Innovation Efficiency		Pure Technical Efficiency		Scale Efficiency		Scale Returns	
	Before	After	Before	After	Before	After	Before	After
000709	1.000	0.635	1.000	0.968	1.000	0.656	-	irs
002049	0.942	0.607	0.943	0.802	0.999	0.757	drs	irs
002271	1.000	0.880	1.000	0.935	1.000	0.941	-	irs
002282	1.000	1.000	1.000	1.000	1.000	1.000	-	-
002350	1.000	1.000	1.000	1.000	1.000	1.000	-	-
300016	0.919	1.000	1.000	1.000	0.919	1.000	drs	-
300026	1.000	1.000	1.000	1.000	1.000	1.000	-	-
300075	0.352	0.032	0.385	0.500	0.916	0.063	irs	irs
300107	0.365	0.026	0.388	0.566	0.943	0.045	irs	irs
300119	0.405	0.036	0.421	0.526	0.962	0.068	irs	irs
002579	0.494	0.045	0.506	0.640	0.976	0.071	irs	irs
300137	0.580	0.104	0.587	1.000	0.987	0.104	irs	irs
300138	0.503	0.110	0.520	0.565	0.967	0.195	drs	irs
300229	0.550	0.244	1.000	0.562	0.550	0.434	drs	irs
300255	1.000	0.149	1.000	0.719	1.000	0.207	-	irs
300271	0.956	0.174	0.968	0.607	0.988	0.287	irs	irs
300365	1.000	0.265	1.000	0.671	1.000	0.395	-	irs
300371	1.000	0.290	1.000	0.716	1.000	0.405	-	irs
300406	1.000	0.340	1.000	0.596	1.000	0.570	-	irs
300407	1.000	0.573	1.000	0.648	1.000	0.884	-	irs
300428	1.000	1.000	1.000	1.000	1.000	1.000	-	-
300455	1.000	0.049	1.000	0.638	1.000	0.076	-	irs
300485	0.701	0.022	0.958	0.660	0.731	0.034	irs	irs
300496	1.000	0.051	1.000	0.666	1.000	0.076	-	irs
600008	0.754	0.036	0.862	0.657	0.875	0.054	irs	irs
600055	0.587	0.027	0.753	0.697	0.780	0.039	irs	irs
600056	0.861	0.059	0.901	0.698	0.955	0.085	irs	irs
600062	0.658	0.068	0.701	0.565	0.938	0.120	irs	irs
600135	0.901	0.016	0.969	0.703	0.930	0.022	irs	irs
600161	0.888	0.015	0.908	0.528	0.978	0.029	irs	irs
600195	0.884	0.024	0.899	0.601	0.983	0.040	irs	irs
600206	0.833	0.024	0.842	0.558	0.990	0.043	irs	irs
600271	0.835	0.040	0.858	0.549	0.973	0.072	irs	irs
600329	0.773	0.037	0.806	0.843	0.959	0.043	irs	irs
600409	0.800	0.023	0.811	0.664	0.987	0.035	irs	irs
600429	0.544	0.018	0.938	0.898	0.580	0.020	irs	irs
600468	0.616	0.007	1.000	0.780	0.616	0.008	irs	irs
600480	0.571	0.059	1.000	1.000	0.571	0.059	irs	irs
600535	0.580	0.047	0.926	0.824	0.627	0.058	irs	irs
600560	0.619	0.095	0.886	0.651	0.699	0.146	irs	irs
600582	0.355	0.044	0.571	0.626	0.622	0.070	irs	irs
600583	0.357	0.029	0.525	0.596	0.680	0.048	irs	irs
600717	0.659	0.080	0.680	0.557	0.969	0.143	irs	irs
600803	0.645	0.091	0.648	0.658	0.995	0.138	irs	irs
600855	0.551	0.062	0.555	0.616	0.992	0.101	irs	irs
600874	0.677	0.033	0.680	0.509	0.994	0.064	irs	irs
600900	0.707	0.056	0.709	0.393	0.996	0.144	irs	irs
600980	0.766	0.075	0.768	0.507	0.998	0.148	irs	irs
601088	0.794	0.098	0.795	0.376	0.999	0.262	irs	irs
601117	0.414	0.011	0.583	0.376	0.710	0.028	irs	irs
601186	0.478	0.014	0.574	0.389	0.832	0.036	irs	irs
601390	0.467	0.027	0.506	0.410	0.923	0.066	irs	irs
601633	0.499	0.015	0.538	0.587	0.929	0.025	irs	irs
601668	0.481	0.015	0.514	0.378	0.936	0.041	irs	irs
601669	0.434	0.022	0.480	0.351	0.905	0.062	irs	irs
601766	0.400	0.026	0.414	0.383	0.967	0.068	irs	irs
601908	0.571	0.003	1.000	0.440	0.571	0.007	irs	irs
601985	0.450	0.003	1.000	0.352	0.450	0.008	irs	irs
603019	0.613	0.011	0.960	0.447	0.638	0.025	irs	irs
603126	1.000	0.083	1.000	0.438	1.000	0.190	-	irs
603698	1.000	0.042	1.000	0.385	1.000	0.109	-	irs
603969	1.000	0.035	1.000	0.615	1.000	0.057	-	irs
603979	0.495	0.003	0.733	0.416	0.675	0.007	irs	irs

Note:"drs" represents decreasing scale returns, while "irs" represents increasing scale returns,

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Compared to the original calculation results, the results of the sample of listed companies in the Beijing-Tianjin-Hebei region after excluding environmental factors and random variable factors show a significant decrease in the average innovation efficiency and scale efficiency, as can be seen from Fig. 1 and Fig. 3. However, there is only a small change in pure technical efficiency compared to innovation efficiency and scale efficiency, as can be seen from Fig. 2. Therefore, the original model has overestimated the innovation efficiency, which does not truly reflect the innovation efficiency level of the listed companies in the Beijing-Tianjin-Hebei region.

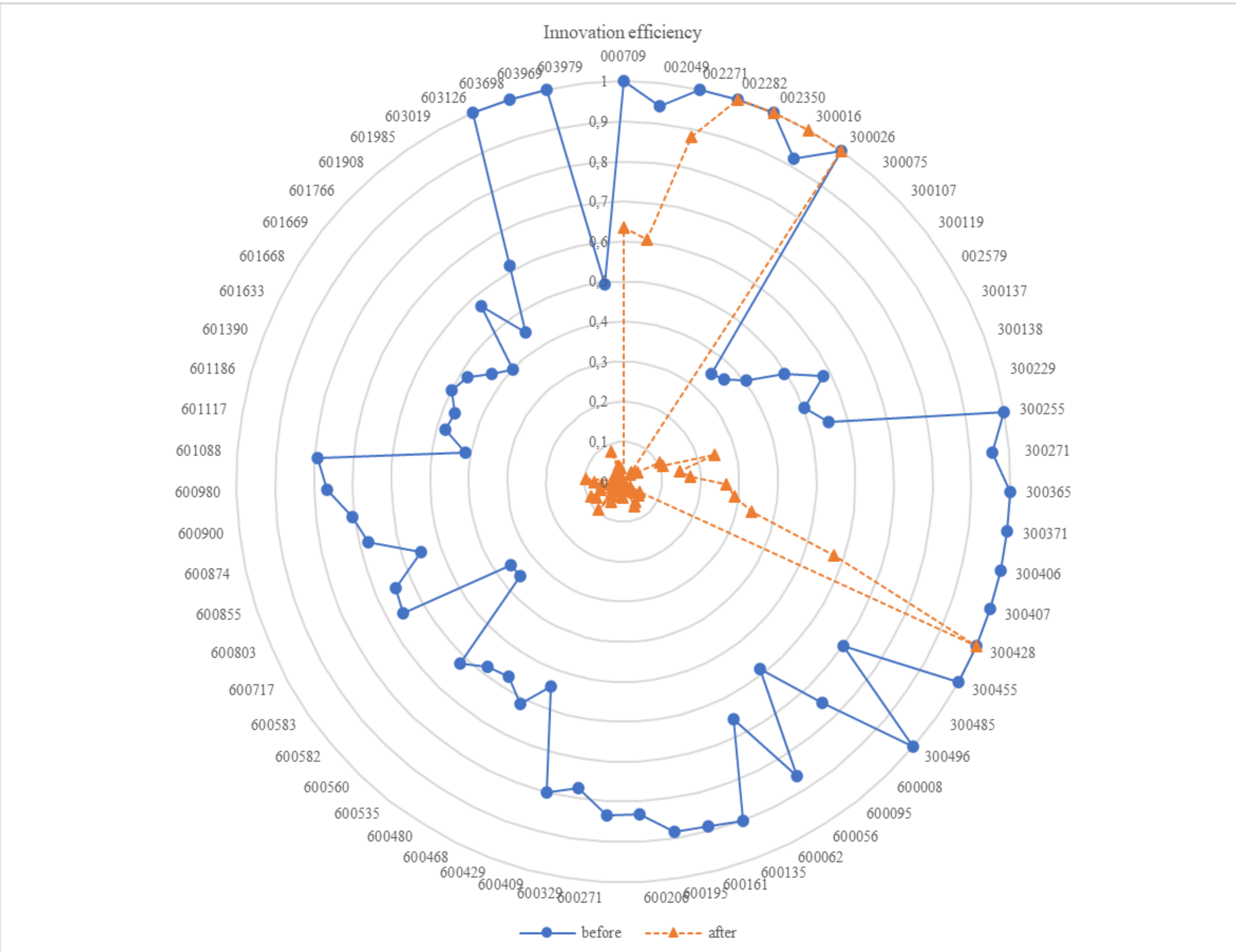

Fig 1. Comparison of innovation efficiency before and after adjustment

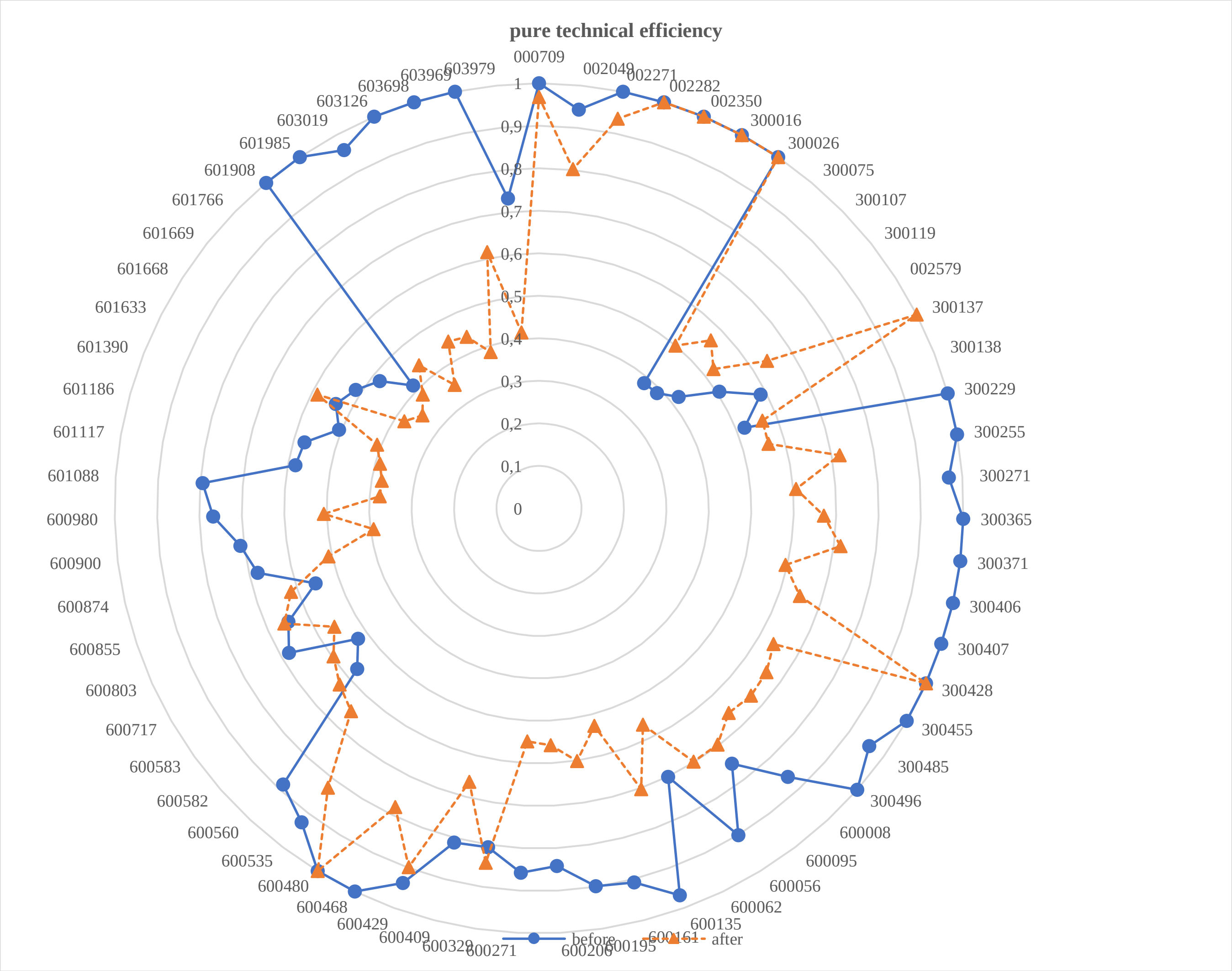

Fig 2. Comparison of pure technical efficiency before and after adjustment

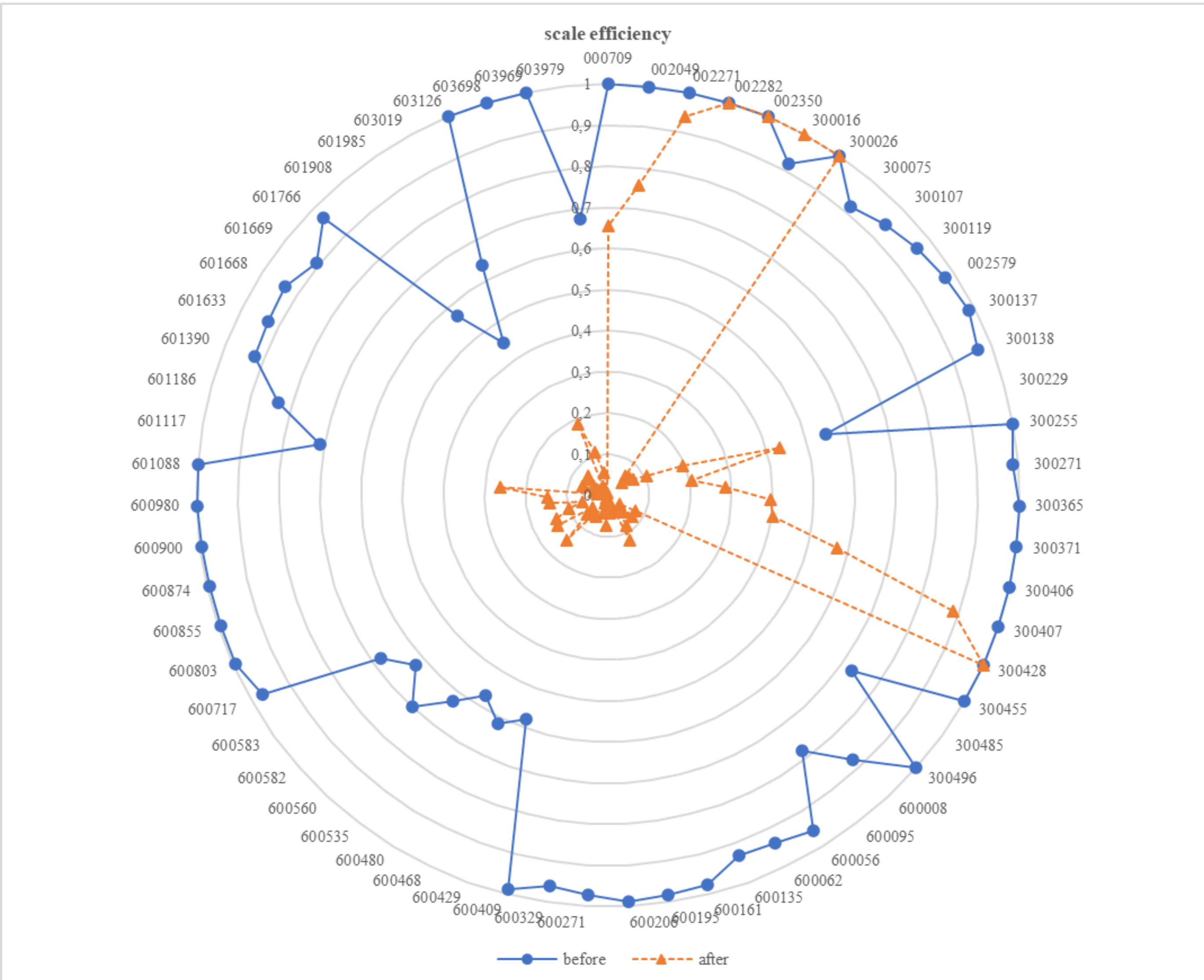

Fig. 3. Comparison of scale efficiency before and after adjustment

Innovation Efficiency

After making necessary adjustments, it can be observed that there exist five companies, which constitute 7.93% of the sample, that have not experienced any change in their innovation efficiency. Additionally, one company, accounting for 1.59% of the sample, has witnessed an increase in its innovation efficiency. This specific company, identified as 300016, has exhibited a notable increase of 8.81%. Conversely, most of the companies, comprising 90.48% of the sample, have displayed a decrease in their innovation efficiency. Among these companies, the one with the most significant decrease is 603979, with a substantial decline of 99.40%. The findings indicate that most companies have shown a declining trend in innovation efficiency following the processing. Furthermore, it is worth noting that most of the companies possess innovation efficiency values lower than 0.1, with only eight listed companies surpassing an innovation efficiency of 0.6. In light of the adjustments

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made, five companies now exhibit an innovation efficiency of 1, while three companies fall within the range of 0.6 to 1 in terms of innovation efficiency. An additional nine companies have an innovation efficiency between 0.1 and 0.6. The remaining 46 companies continue to have an innovation efficiency lower than 0.1. These results underscore the importance of placing emphasis on the innovation level of enterprises. Among the 16 leading companies in innovation, only four companies have managed to maintain their position at the forefront of innovation following the adjustments. These companies are identified as 002282, 002350, 300026, and 300428. Notably, 300016 remains the sole company that remains at the forefront of innovation after the adjustments. A comparison with the results obtained prior to the processing reveals an overestimation in the computation of innovation efficiency.

<u>Pure Technical Efficiency</u>

After making necessary adjustments, there exist 6 companies (9.52% of the entire dataset) that exhibit unaltered pure technical efficiency. Additionally, there are 10 companies (15.873% of the entire dataset) that demonstrate an escalated level of pure technical efficiency, with the highest observed increase being 300137, corresponding to a surge of 70.36%. Conversely, 47 companies (74.603% of the entire dataset) indicate a decrease in pure technical efficiency, with the most substantial decline identified as 601985, reflecting a reduction of 64.80%. Notably, the primary trend following the adjustments remains the decline in pure technical efficiency. Specifically, the pure technical efficiency of 29 companies within the sample falls below 0.6, while 7 companies achieve a pure technical efficiency of 1. Most of the companies fall within the medium level category.

<u>Scale Efficiency</u>

After making the necessary adjustments, it is observed that there are 4 companies (6.35% of the total sample) that have maintained the same level of scale efficiency. Additionally, 1 company (1.59% of the total sample), namely 300016, has shown an increase in scale efficiency by 8.81%. On the other hand, most of the companies, specifically 58 companies (92.06% of the total sample), have experienced a decrease in scale efficiency. Among these, the company with the most significant decrease is 603979, with a decrease of 98.96%. Upon further analysis, it is found that the average scale efficiency of the 63 listed companies has decreased from 0.891 to 0.222 after the adjustments. This decline in scale efficiency is identified as the primary factor contributing to a significant decrease in innovation efficiency. Furthermore, out of the 63 companies, a total of 41 companies exhibit a scale efficiency of less than 0.1.

<u>Scale Returns</u>

In the sample of 63 companies, the number of companies displaying unchanged returns to scale has decreased from 16 to 5. Within this group, there are 4 companies that demonstrated constant returns to scale before adjustment, specifically 002282, 002350, 300026, and 300428. Prior to adjustment, 4 companies showed increasing returns to scale. Among the remaining companies (after adjustment), 58 of them demonstrated increasing returns to scale, with 12 displaying constant returns to scale before adjustment, 3 showing decreasing returns to scale, and 43 displaying increasing returns to scale. These findings suggest that the pure technical efficiency and scale efficiency of these 58 companies have not yet reached optimal levels. Improvement can be achieved by introducing research talent, increasing research funding, enhancing the transformation of innovative accomplishments, and optimizing scientific and technological facilities. For companies with a scaling efficiency lower than 0.1, prioritizing the expansion of enterprise scale can enhance innovation efficiency. Furthermore, the enhancement of scale efficiency resulting from the expansion of enterprise scale plays a crucial role in improving innovation efficiency.

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Malmquist Index

Based on the data calculated from the DEA-BCC model in the previous stage, we used the Malmquist Index to measure the technical efficiency, technical progress, pure technical efficiency, scale efficiency, and total factor productivity of listed companies in the Beijing-Tianjin-Hebei region from 2015 to 2021, and the results are shown in Table 6.

Table 6. DEA-Malmquist Index Analysis of Sample Companies from 2015 to 2021

Stock Code	Technical Efficiency（effch）	Technical Progress（techch）	Pure Technical Efficiency（pech）	Scale Efficiency（sech）	Total Factor Productivity（tfpch）	Rank
000709	0.992	0.998	0.975	1.017	0.990	47
002049	1.013	0.868	1.000	1.012	0.879	53
002271	0.978	0.891	0.986	0.992	0.872	55
002282	1.000	1.059	1.000	1.000	1.059	43
002350	0.977	0.900	0.986	0.991	0.879	53
300016	1.000	0.938	1.000	1.000	0.938	52
300026	1.000	0.962	1.000	1.000	0.962	49
300075	1.778	0.839	1.122	1.585	1.492	14
300107	1.829	0.883	1.095	1.669	1.615	8
300119	1.743	0.925	1.113	1.566	1.612	9
002579	1.667	0.987	1.077	1.548	1.646	3
300137	1.459	1.073	1.000	1.459	1.566	10
300138	1.426	0.925	1.089	1.310	1.319	27
300229	1.216	0.941	1.076	1.131	1.145	40
300255	0.995	0.761	1.040	0.957	0.757	59
300271	0.695	0.805	1.039	0.669	0.559	63
300365	0.959	0.905	1.045	0.918	0.868	56
300371	0.760	0.837	1.057	0.719	0.636	60
300406	0.981	0.779	1.050	0.934	0.764	58
300407	0.679	0.831	1.064	0.638	0.564	62
300428	0.686	0.832	0.999	0.687	0.571	61
300455	1.387	0.817	0.989	1.402	1.132	42
300485	1.573	0.811	0.987	1.594	1.276	33
300496	1.485	0.853	1.011	1.469	1.266	34
600008	1.606	0.815	1.012	1.587	1.309	28
600055	1.649	0.819	0.999	1.651	1.352	24
600056	1.511	0.885	1.014	1.489	1.337	26
600062	1.534	1.056	1.100	1.395	1.620	6
600135	1.807	0.807	1.030	1.755	1.457	19
600161	1.885	0.873	1.064	1.771	1.645	4
600195	1.763	0.832	1.044	1.689	1.466	17
600206	1.582	0.821	1.026	1.541	1.298	29
600271	1.563	0.860	1.047	1.493	1.345	25
600329	1.688	0.865	1.029	1.641	1.460	18
600409	1.763	0.857	1.043	1.691	1.511	13
600429	0.895	1.074	0.959	0.934	0.962	49
600468	1.351	0.872	0.969	1.394	1.179	38
600480	1.376	0.933	0.983	1.400	1.284	32
600535	1.263	0.921	0.997	1.267	1.163	39
600560	1.047	0.903	1.002	1.045	0.946	51
600582	1.478	0.852	1.017	1.452	1.259	35
600583	1.002	1.000	1.015	0.987	1.001	45
600717	1.438	1.085	1.066	1.349	1.560	11
600803	1.382	1.012	1.037	1.332	1.398	20
600855	1.588	1.062	1.084	1.465	1.687	2
600874	1.367	1.019	1.047	1.306	1.394	21
600900	1.490	1.027	1.089	1.368	1.530	12
600980	1.251	1.034	1.028	1.217	1.293	30
601088	0.981	0.995	1.029	0.954	0.977	48
601117	2.130	0.763	1.177	1.810	1.626	5
601186	2.037	0.795	1.170	1.741	1.620	6
601390	1.763	0.785	1.136	1.552	1.383	22
601633	1.650	0.735	1.093	1.510	1.213	37
601668	1.657	0.777	1.146	1.446	1.287	31
601669	1.614	0.753	1.151	1.402	1.216	36
601766	1.161	0.857	1.137	1.022	0.995	46
601908	1.584	0.931	1.067	1.485	1.474	16
601985	1.941	0.768	1.064	1.823	1.489	15

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603019	1.376	0.829	1.062	1.296	1.141	41
603126	0.913	0.892	1.058	0.863	0.815	57
603698	1.142	0.908	1.043	1.096	1.037	44
603969	1.348	1.008	1.056	1.276	1.359	23
603979	2.129	0.831	1.053	2.022	1.769	1
Mean	1.329	0.889	1.046	1.271	1.182	
Maximum value	2.130	1.085	1.177	2.022	1.769	
Minimum value	0.679	0.735	0.959	0.638	0.559	

From Table 6, we can observe that among the 63 firms, 601117 possesses the highest index of technical efficiency, standing at 2.13. Similarly, 600717 exhibits the highest index of technical progress, reaching 1.085. Furthermore, 601117 displays the highest index of pure technical efficiency, amounting to 1.177. However, 603979 achieves the highest index of scale efficiency, 2.022. Notably, it also attains the highest index of total factor productivity, standing at 1.769. The average index of total factor productivity for the 63 listed companies is 1.182. It is worth mentioning that 18 companies have a total factor productivity index below 1, accounting for 28.57% of the sample size. Conversely, 45 companies have a total factor productivity index exceeding 1, accounting for 71.43% of the sample size. This implies that the innovation efficiency of most listed companies in the Beijing-Tianjin-Hebei region is increasing, while their production technology and management level are advancing. However, only a small number of companies are witnessing a decline in their production technology and management level. The strong correlation between the total factor productivity index and the scale index suggests that scale efficiency is a pivotal factor influencing the total factor productivity of listed companies in the Beijing-Tianjin-Hebei region. This finding is consistent with the conclusion derived from the DEA-BCC model in the previous stage. The pure technical efficiency index of the 63 companies experiences minor fluctuations around 1, whereas the scale efficiency index displays more significant variations, with a disparity of 1.384 between the maximum and minimum values.

To provide a clearer depiction of the elements influencing the efficacy of innovation in publicly traded firms, as well as identify the areas in which their innovation efficiency is lacking, we utilize a threshold of 1 to classify the companies into distinct categories of technological advancement, technological progression and enhancement, enhancement of technical efficiency, and regressive technological innovation, as demonstrated in Table 7.

Table 7. Situations of Enterprise Science and Technology Innovation Progress

Type	Classification criteria	Stock Code of Companies
Advanced type of technological innovation	Technical efficiency ≥ 1 Technological progress ≥ 1	002282、300137、600062、600583、600717、600803、600855、600874、600900、600980、603969
Technological progress and improvement	Technical efficiency≥1 0≤Technological progress≤ 1	002049、300016、300026、300075、300107、300119、300120、300138、300229、300455、300485、300496、600008、600055、600056、600135、600161、600195、600206、600271、600329、600409、600468、600480、600535、600560、600582、600583、601117、601186、601390、601633、601668、601669、601766、601908、601985、603019、603698、603979
Technical efficiency improvement	0 ≤Technical efficiency≤1 Technological progress≥1	002282、600429
Backward type of technological innovation	0≤Technical efficiency≤1 0≤Technological progress≤1	000709、002271、002350、300016、300026、300255、300271、300365、300371、300406、300407、300428、601088、603126

From the table 7, we can see that there are 11 companies belonging to advanced type of technological innovation, accounting for 17.46% of the total sample size, 36 are the type of technological progress and improvement, accounting for 57.14%, 2 are regarded as technical efficiency improvement, accounting for 3.17%, and 14 are backward type of technological innovation, accounting for 22.22%. More than half of the companies are the type of technological progress and improvement, indicating that their R&D scale, enterprise management, and resource allocation are relatively good, and improving their innovation level and enhancing the ability of scientific research

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personnel are of great help in promoting innovation efficiency. For those who are technical efficiency improvement, how to improve their R&D scale, accelerate scientific research and innovation progress, and speed up the transformation of achievements should be their focus. Those companies that are an advanced type of technological innovation have a high level of technical efficiency and progress, making them a reference for other related companies, while for a backward type of technological innovation, there is enormous potential for improvement and a lot of room for improvement. Therefore, the technological efficiency and progress of these companies should be the focus of attention in their future development.

Tobit Regression Model

Based on the previous DEA third-order model research, we evaluated the innovation efficiency of companies from six aspects. The explanatory variables were selected from two aspects: internal factors of companies and external environmental factors. The former included the number of R&D personnel, R&D financial input, enterprise scale, and equity concentration, while the latter covered the degree of opening to the outside world, the level of economic development, and policy support of the location. The variable selection is shown in Table 8.

Table 8. Factors Influencing Innovation Efficiency of Sample Companies

Variables		Symbol	Definition
The explained variable	Technological innovation efficiency	TE	Input-output ratio of technological innovation
The explanatory variables	Enterprise size	Size	Natural logarithm of total assets
	Ownership concentration	Top	Shareholding ratio of the largest shareholder
	Years of establishment	Time	Date of establishment of the company
	Property nature	Type	State-owned enterprise or non-state-owned enterprise
	Level of regional openness	Open	Actual utilization of FDI in cities
	Level of economic development	Level	Per capita GDP of the city
	Financial expenditure	Expense	Financial expenditure of the city

The outcomes acquired from the Tobit regression model are displayed in Table 9. Based on the discoveries of the Tobit analysis, it can be inferred that:

- An increased level of regional openness can offer enterprises a broader array of technology communication channels, thereby ensuring strong guarantees for their workforce, technology, and financial needs, not just for the substantial funding required for innovation, but also for regular business operations.

- The policies and financial support provided by the government in relation to innovation exert a notable impact on enterprises. Simultaneously, although governmental backing can address the imbalance in innovation resources, it may also lead to enterprises violating regulations regarding the use of subsidized funds, excessively depending on government aid, and intensifying their research stagnancy.

Table 9. Tobit Analysis Results of Factors Influencing Innovation Efficiency of Sample Companies

Variable	Coefficient	Standard Deviation	T Value	P Value
Enterprise size	0.4686	0.805	0.58	0.561
Ownership concentration	-0.0542	0.105	-0.52	0.606
Years of establishment	-4.4643	5.405	-0.83	0.409
Property nature	-4.1441	2.778	-1.49	0.137
Level of regional openness	-13.6366***	4.724	-2.89	0.004
Level of economic development	9.1761*	5.434	1.69	0.092
Financial expenditure	14.4747***	5.526	2.62	0.009
Constant	-22.8326	47.262	-0.48	0.629

*Note: * * *, * *, * respectively represent significant confidence levels of 1%, 5%, and 10%. The values in parentheses are T values.*

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5. Summary and Conclusions

This paper has investigated the innovation efficiency of listed companies in the Beijing-Tianjin-Hebei region from 2015 to 2021. The study aims to identify factors that affect innovation efficiency and provide insights for policymakers and company management to improve innovation efficiency.

The novelty of this research lies in its focus on the Beijing-Tianjin-Hebei Economic Zone, a significant planned economic zone in China. The region is known for its concentration of cities and comprehensive strength, making it an important contributor to China's economic growth. The study explores the innovation efficiency of listed companies within this region and analyzes the factors influencing their innovation performance.

The methodology employed in the research includes the use of Data Envelopment Analysis (DEA), which is a non-parametric method for measuring innovation efficiency. The traditional DEA model is enhanced with several improved models, such as the two-stage DEA, three-stage DEA model, DEA-R, and ultra-efficiency DEA. These models help evaluate the innovation efficiency of the listed companies and provide a more comprehensive reflection of innovation efficiency under multiple factors.

The results of the analysis indicate that, after adjusting the data, there is a significant decrease in scale efficiency and a slight decline in pure technical efficiency among the listed companies. This suggests that the innovation efficiency of these companies may have been overestimated. The study also reveals that the business environment, enterprise nature, equity concentration, and urban financial expenditure have a positive impact on innovation efficiency. Longer-established companies face challenges in improving their innovation efficiency, while most companies show improvements in technical efficiency.

Overall, this research provides valuable insights into innovation efficiency among listed companies in the Beijing-Tianjin-Hebei region. It contributes to a more comprehensive understanding of the factors that influence innovation efficiency and offers practical implications for future development. The study highlights the importance of considering scale efficiency and the business environment when evaluating innovation efficiency. It suggests that policymakers and company management should prioritize the enterprise's nature, equity concentration, and urban financial expenditure to cultivate innovation efficiency.

The research has certain limitations. It focuses specifically on listed companies in the Beijing-Tianjin-Hebei region, which may limit the generalizability of the findings to other regions or types of companies. Additionally, the study relies on secondary data and the application of DEA models, which may have inherent limitations and assumptions.

Further research directions could include expanding the analysis to a broader range of regions or industries to gain a more comprehensive understanding of innovation efficiency. Additionally, qualitative research methods such as interviews or case studies could provide deeper insights into the factors influencing innovation efficiency. Moreover, exploring the role of specific innovation strategies or policies in improving innovation efficiency would be valuable for future research.

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Appendix: The Sample of listed companies: Stock codes and company names

000709: 牛庄股份/Neusoft Group 002049: 紫光国芯/McNair Technology 002271: 东方雨虹/EASTERN UNITED. 002282: 南岭民爆/SSA SICHUAN MINJIANG/Minjiang Acoustic 002350: 北京科锐/BJCCRRC 300016: 北陆药业/Northern Land Pharmaceutical 300026: 红日药业/Hongri Acron Chemical Joint Stock 300075: 数字政通/Simcere Digital Public Health Technology 300107: 延江股份/Yanjiang Stock 300119: 瑞普生物/Ripos Biological Medicine 300120: 经纬辉开/Jingwei Fuyuan Corporation 300137: 先河环保/Anhui Advance Electrode Material 300138: 晨光生物/Chen Guangbio Pharmaceutical 300229: 拓尔思/Trueheld Optics 300255: 常山药业/Changshan Biochemical Pharmaceutical 300271: 华宇软件/Huayu Software 300365: 恒华科技/Henghua Technology 300371: 汇中股份/Huizhong 300406: 九强生物/Jiuqiang Biotechnology 300407: 凯发电气/Kaifa Technology 300428: 四通新材/Sitong New Material 300455: 康拓红外/Contron Infrared 300485: 赛升药业/Sino Biopharmaceutical 300496: 中科创达/Zhongke Chuangda Soft Power Technology 600008: 首创股份/Beijing Capital Development 600055: 万东医疗/Wandong Medical Technology 600056: 中国医药/China National Pharmaceutical Group 600062: 华润双鹤/Huarun Double-Crane Pharmaceutical 600135: 乐凯胶片/LuckFilm 600161: 天坛生物/Pharmaceutical Industry Group of Tian Tan Bio-Medical 600195: 中牧股份/China National Animal Husbandry 600206: 有研新材/Youneng New Materials 600271: 航天信息/Aeolus Technology	600329: 中新药业/China National Resources Development Holdings 600409: 三友化工/Beijing Aircraft Instrumentation Research Institute Chemical Factory 600429: 三元股份/Sanyuan Foods 600468: 百利电气/Belle Electric 600480: 凌云股份/Lingyun Industrial Corp. Limited 600535: 天士力/Tianshi Biological Compositions Jilin 600560: 金自天正/Zhenjiang Gold Orthopedic Joint Stock 600582: 天地科技/Tiandi Technology 600583: 海油工程/Offshore Oil Engineering 600717: 天津港/Tianjin Port Development Holdings 600803: 新奥股份/Donaldson Company 600855: 航天长峰/Analytical Instrument 600874: 创业环保/China Trends Holdings 600900: 长江电力/Yangtze Power 600980: 北矿科技/Northern Mine Technology 601088: 中国神华/China Shenhua Energy 601117: 中国化学/China National Chemical Corporation 601186: 中国铁建/China Railway Construction Corporation 601390: 中国中铁/China Railway Group Limited 601633: 长城汽车/Great Wall Motor 601668: 中国建筑/China State Construction Engineering Corp.. 601669: 中国电建/China Huadian Corporation 601766: 中国中车/China CNR Corporation 601908: 京运通/Ocienstra Intelligent System 601985: 中国核电/China National Nuclear Corporation 603019: 中科曙光/Zhongke Shuguang Information Industry 603126: 中材节能/CNGC HEBEI JIANJUN WEIYE ENERGY SAVING 603698: 航天工程/China Aerospace Times Electronics 603969: 银龙股份/Yinlong New Energy 603979: 金诚信/Jincheng Holdings

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