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Operational Efficiency of Pharmaceutical Companies in China: Based on Three-Stage DEA with Undesirable Outputs

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Abstract: After a period of rapid growth, China's pharmaceutical industry is facing multiple challenges, including insufficient innovation and severe pollution. Current research on the efficiency of pharmaceutical companies in China primarily focuses on financial or innovation aspects. Therefore, a holistic approach to operational efficiency is needed. To measure the operational efficiency of pharmaceutical companies in China more accurately and holistically, while accounting for environmental pollution, this study employs a three-stage Data Envelopment Analysis (DEA) model with undesirable outputs to evaluate efficiency across five dimensions: market performance, profitability, financial risk control, innovation, and sustainability. This approach integrates financial, innovation, and sustainability indicators to provide a more industry-specific framework for efficiency measurement. Furthermore, integrating with Stochastic Frontier Analysis (SFA) allows for revealing the impact of environmental factors on efficiency. The results show that both technical efficiency (TE) and pure technical efficiency (PTE) are relatively low in the first and third stages, with significant regional disparities. After excluding environmental factors, some regions—typically economically developed areas—showed improved overall efficiency. This indicates that the local environment in these regions is not conducive to the development of pharmaceutical enterprises. The SFA results further demonstrate that investments in education and high-level talent significantly enhance efficiency, whereas pollutant emissions and per capita income reduce operational efficiency. The findings suggest that local governments should enhance the operational efficiency of pharmaceutical enterprises by investing in education, attracting skilled talent, and improving waste infrastructure. Additionally, less efficient firms are encouraged to optimize resource allocation to achieve higher efficiency.

Keywords: efficiency analysis; pharmaceutical operations; sustainable development; innovation efficiency; environmental impacts

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1. Introduction

The pharmaceutical industry is a cornerstone of public health and economic stability, contributing significantly to national and international welfare. Globally, the industry is witnessing rapid advancements driven by increasing demand for innovative drugs, stringent environmental regulations, and evolving patient needs. In this context, China, as the world's second-largest healthcare market and one of the fastest-growing, provides a critical case study. Its pharmaceutical sector mirrors global challenges, including rising research and development (R&D) costs, regulatory pressures, and sustainability concerns, which are also faced by other major markets such as the United States and the European Union [1].

According to the Pharmaceutical Industry Economic Operation Report, Chinese residents' per capita healthcare spending of Chinese residents rose from 188.3 Chinese Yuan (CNY) in 2000 to 2120 CNY in 2022, marking an 11.2-fold increase and a clear upward trend overall. Although the share of per capita healthcare spending in overall consumer spending has shown slight variations and notable fluctuations, it has generally increased, rising from 6.46% in 2000 to 8.64% in 2022.

Although the Chinese pharmaceutical industry has made significant progress in recent years, it still faces numerous challenges. The first challenge is its lack of international competitiveness. Despite an increase in global market share, China accounts for approximately 2%, ranking 15th worldwide. Furthermore, its pharmaceutical trade competitiveness is ranked 47th globally [2]. Moreover, in 2023, only four Chinese pharmaceutical companies were ranked in the world's top 50 pharmaceutical enterprises. These figures highlight the substantial gap between China and the leading global pharmaceutical markets.

Secondly, the level of R&D investment in China needs to be increased. Data from Chinese-listed companies indicate that the research and development (R&D) expenditure ratio increased from 3.25% in 2013 to 7.21% in 2022. However, this remains significantly below global standards. In 2021, the average global R&D investment ratio stood at 27%, with the United States reaching 34% and Europe at 22% [3]. This considerable shortfall in R&D expenditure constitutes a major obstacle to advancing innovative pharmaceutical development in China. According to data from the National Medical Products Administration (NMPA), the share of innovative drugs in China has consistently remained below 5% over the past two decades, indicating the industry's long-standing reliance on generic drugs.

Thirdly, the industry comprises many enterprises with limited economies of scale, leading to a low industry concentration. Currently, the concentration of the pharmaceutical market in China is 3.9%, while Europe's concentration is 30.5% (IBIS World Research Report) [4].

Additionally, China's high-end pharmaceutical supply remains insufficient, with industry development primarily focused on generic drugs and active pharmaceutical ingredients (APIs) [5,6]. The centralized procurement policies for generics have contributed to increasing loss-making firms in the domestic market (Pharmaceutical Industry Operation Report).

Meanwhile, pollution from the pharmaceutical industry has become a global issue, drawing widespread attention worldwide [7]. The production of pharmaceutical intermediates generates significant amounts of chemical oxygen demand (COD), biological oxygen demand (BOD), and waste gases, causing severe environmental pollution [8–10]. Additionally, during the production of APIs and final products, active pharmaceutical residues can enter wastewater systems, resulting in highly complex wastewater compositions. Even low concentrations of these residues can lead to serious environmental consequences [11].

Various countries have implemented measures to address pharmaceutical industry pollution. In the United States, the disposal of pharmaceutical waste is regulated by the Environmental Protection Agency, the Drug Enforcement Administration, and the Occupational Safety and Health Administration (OSHA). In Japan, collaborative efforts began in 2006, with the Resource Conservation and Waste Management groups working alongside the Federation of Pharmaceutical Manufacturers' Associations of Japan to promote the proper disposal of solid pharmaceutical waste [12].

To address the issue of pollution, China has proposed the strategies of "carbon peak and carbon neutrality" alongside the goal of "synergizing pollution reduction and carbon emission control", elevating the importance of ecological and environmental protection to an unprecedented level [13].

To address the issues of low innovation capacity and high pollution in China's pharmaceutical industry, the Chinese government released the Guiding Opinions on Promoting the Green Development of the API Industry (2020) [14], which aims to advance the green development of the API sector, improve clean production levels, reduce pollutant emissions, and promote sustainable industrial growth. Later, the 14th Five-Year Plan for the Development of the Pharmaceutical Industry (2022) [15] outlines a clear direction for the sector, emphasizing innovation-driven growth, enhancing core industrial competitiveness, and promoting green, sustainable development.

Given that multiple inputs and outputs characterize the pharmaceutical industry, its production process involves not only financial outputs, such as operating revenue and profit but also long-term indicators, such as patents and manufacturing permits. Simultaneously, the industry inevitably generates waste emissions. Furthermore, China's development is uneven, with distinct economic, environmental, and demographic characteristics across regions. Therefore, understanding the impact of environmental factors on efficiency is equally significant.

To measure the operational efficiency of China's listed pharmaceutical companies comprehensively and accurately and to reveal the impact of environmental factors on efficiency, this study employs a three-stage Data Envelopment Analysis (DEA) approach with undesirable outputs.

This method effectively incorporates financial and innovation indicators as desirable outputs and waste emissions as undesirable outputs into the evaluation. It separates the influence of environmental factors from managerial efficiency, reducing interference from external and random factors. This is particularly applicable to China's pharmaceutical industry, which has multiple inputs and outputs and faces significant regional environmental disparities.

In this study, "undesirable outputs" refer to negative by-products of production processes, such as pollutant emissions and waste, which are factored into efficiency evaluations. "Technical efficiency" (TE) refers to a company's ability to maximize output through the effective use of input resources under given production conditions. "Pure technical efficiency" (PTE) refers to the efficiency a company achieves based solely on its technical and managerial capabilities, excluding the impact of scale.

2. Literature Review

2.1. An Overview of Efficiency Theory and Evaluation Methods

Pareto first introduced the concept of efficiency in 1896, defining it as an ideal state of resource allocation known as "Pareto Optimality". Later, Farrell (1957) [16] developed the efficiency evaluation theory, dividing efficiency into technical efficiency and allocative efficiency, thereby establishing a theoretical foundation for assessing operational efficiency from the perspectives of inputs and outputs. Based on this theory, two kinds of methods for efficiency evaluation were applied: parametric and non-parametric approaches.

Parametric methods for evaluating operational efficiency include the Distribution-Free Approach (DFA), Thick Frontier Approach (TFA), Recursive Thick Frontier Approach (RTFA), and Stochastic Frontier Analysis (SFA), with SFA being the most widely used.

Stochastic Frontier Analysis (SFA), introduced by Aigner and Lovell in 1977 [17], is a parametric method that decomposes the error term into two components: random error, which reflects external factors such as weather, and inefficiency, which reflects internal factors such as managerial performance. SFA evaluates the efficiency of decision-making units (DMUs) by accounting for stochastic variation and estimating technical efficiency, making it highly applicable across various fields, including agriculture, environmental studies, and general business operations. Its widespread adoption is supported by numerous studies, such as those by [18–21].

However, one notable disadvantage of Stochastic Frontier Analysis (SFA) is that researchers are required to select the functional form of the production model, which introduces the risk of incorrect specification [22]. Additionally, assumptions must be made regarding the production function (e.g., Cobb–Douglas, Translog, or Transcendental) as well as the distribution of the error term [23]. Consequently, the results may exhibit a degree of subjectivity [24].

Another widely used approach for efficiency evaluation is the non-parametric method, represented by Data Envelopment Analysis (DEA). Proposed by A. Charnes and W.W. Cooper in 1978, DEA is a non-parametric technique designed to evaluate the relative efficiency of multiple Decision-making units (DMUs). Its principle lies in constructing a "best-practice frontier", where the most efficient DMU serves as a benchmark. Other DMUs are then compared against this benchmark to calculate their relative efficiency [25].

Compared to parametric methods, DEA offers significant advantages, including the absence of a need to assume a specific production function, no requirement for uniform measurement scales between inputs and outputs, and no assumptions about relationships among input variables. These advantages enable DEA to overcome many limitations inherent in parametric methods for efficiency evaluation.

Over the past four decades, DEA has been extensively applied across various fields. Examples include the evaluation of pharmaceutical companies' operational efficiency [26], the operational efficiency of regional airports [27], the innovation performance of the pharmaceutical industry [28], the efficiency assessment of national commercial banks [29], the innovation efficiency of the artificial intelligence industry [30] the efficiency evaluation of the retail industry [31], and the performance assessment of national health systems [32].

Although DEA does not require the assumption of a specific production function, it still has certain limitations. For instance, the selection of inputs and outputs can involve considerable discretion [33], potentially leading to biased evaluation results. Additionally, DEA is unable to adequately account for external environmental factors and random noise, making efficiency assessment results susceptible to such influences [34,35].

To address the impact of environmental factors and random noise on efficiency, Fried et al. (1999) [36] proposed the three-stage DEA method. This method separates efficiency evaluation into three steps, effectively isolating environmental influences, random error and managerial inefficiency, thereby providing more accurate efficiency measurements. The three-stage DEA method combines the advantages of non-parametric approaches, such as the ability to evaluate multiple inputs and outputs without requiring unified measurement scales, while also addressing the limitations posed by environmental and random noise. Furthermore, it can disentangle managerial inefficiencies [37]. As a result, it has been widely applied in fields such as energy efficiency [38], energy-saving retrofits (Wang et al., 2022), and the efficiency of research institutes [39].

In summary, SFA has the advantage of decomposing environmental influences and random error but is limited by its reliance on predefined functional forms and distributional assumptions. In contrast, DEA excels in handling multiple inputs and outputs without requiring a specific functional form; however, it cannot account for environmental and stochastic errors. Therefore, the combination of these two methods in the three-stage DEA model integrates their respective strengths, offering a more comprehensive evaluation approach.

2.2. Efficiency Evaluation with Undesirable Outputs

Waste in the pharmaceutical industry is unavoidable, primarily due to the inherent characteristics of the sector, particularly in chemical pharmaceuticals, where waste is complex and challenging to manage [8–11]. In the pharmaceutical industry, pollutants are typically classified as undesirable outputs. However, in this field, existing literature has not yet integrated waste into the framework of efficiency evaluation.

The evaluation considering undesirable outputs has been studied relatively early, with diverse methodologies available. For example, some studies ignore the impact of waste entirely [40], while others incorporate waste as an input variable [41]. Additionally, more complex modelling approaches have been proposed, such as the S-Z model [42], techniques based on directional distance functions [43], and Slacks-Based Measure (SBM) DEA models [44]. These methods provide robust tools for efficiency evaluation across various fields and have been widely applied in studies of efficiency with undesirable outputs.

Currently, efficiency evaluations involving undesirable outputs increasingly tend to integrate additional indicators for a more comprehensive assessment of efficiency levels. For instance, Guo et al. (2024) [45] utilized a Super-SBM-DEA model to evaluate regional production efficiency and pollution control efficiency by combining industrial value-added and environmental indicators (e.g., wastewater, solid waste, and sulfur dioxide). Similarly, Jiang et al. (2024) [46] employed a Super-SBM-DEA model using GDP, carbon dioxide, and wastewater emissions as evaluation metrics for overall efficiency assessment. In the agricultural sector, Han and Yang (2024) [47] applied the Meta-frontier Non-Radial Directional Distance Function (NDDF) and Tobit regression models to evaluate agricultural production efficiency, using gross agricultural output as the output variable and incorporating environmental indicators such as water and air pollution. For the energy industry efficiency assessment, Pan et al. (2024) used an improved NDDF and the Global Non-Radial Malmquist–Luenberger Productivity Index (GNMI) to evaluate the power systems industry based on power generation and Carbon Dioxide emissions.

International research has also demonstrated the extensive application of combining economic and environmental indicators. For example, López-Gallego and Herrero-González (2024) [48] employed DEA combined with regression analysis to evaluate the economic and environmental efficiency of 27 EU countries, using carbon dioxide and methane as environmental indicators. Nugraha and Mur (2023) [49] incorporated energy consumption and hazardous waste as input variables when assessing the efficiency of railway manufacturing companies. Gennitsaris and Sofi-anopoulou (2024) [50] combined DEA with Life Cycle Assessment (LCA) to comprehensively evaluate machinery operational efficiency through economic, environmental, and social indicators. In addition, similar approaches integrating economic and environmental indicators to evaluate overall efficiency still exist [51,52].

In summary, the combined evaluation of economic and environmental indicators has become a predominant approach for assessing the efficiency of sectors associated with pollution. However, in the pharmaceutical industry, environmental indicators remain excluded from the efficiency evaluation framework, highlighting a significant research gap.

2.3. The Efficiency Evaluation in Pharmaceutical Companies

Currently, scholars generally study the operational efficiency of pharmaceutical enterprises in China from a single perspective, focusing either on innovation or financial performance.

2.3.1. Evaluation of Innovation Efficiency in Pharmaceutical Enterprises

Innovation is a critical aspect of enterprise management and operations. However, research on the innovation efficiency of pharmaceutical companies remains limited. Xiong and Meng (2019) [53] using BCC-DEA, analyzed the innovation efficiency of China's listed pharmaceutical enterprises, concluding that low pure technical efficiency was the main limiting factor. Compared to TCM and chemical drug companies, biopharmaceutical companies demonstrated higher innovation efficiency. By employing a two-stage DEA model, Hao and Ruan (2022) [54] identified low efficiency in both the technology development and results transformation stages of listed biopharmaceutical enterprises, attributing this inefficiency to redundant R&D investment and excessive patent inputs. Additionally, Qiu et al. (2023) [55] applied a three-stage DEA model to assess regional innovation efficiency in China's pharmaceutical industry. Their findings highlighted that overall innovation efficiency was low and unevenly distributed, with the highest efficiency observed in the eastern and northeastern regions.

Research on innovation in pharmaceutical enterprises has also been conducted internationally. In 2018, Shin et al. [56] employed SFA and multiple frontier analysis to assess the efficiency of 705 pharmaceutical companies in the U.S., concluding that different open innovation (OI) strategies have varying impacts on firms, with the inside-out strategy performing the best in terms of both innovation and efficiency. Schuhmacher et al. (2021) [57] used indicators such as New Molecular Entities (NMEs) to measure output and found that companies like Pfizer and Merck exhibited the highest efficiency among global pharmaceutical enterprises. However, in a subsequent study, Schuhmacher et al. (2023) [58] argued that the R&D efficiency of these global giants is currently facing significant challenges.

There are notable differences in the selection of output indicators between Chinese and international scholars. Chinese studies predominantly use patent applications and new product sales as output indicators. In contrast, international research employs a broader range of metrics, including approvals for NMEs, publication impact factors, and financial indicators.

According to the Drug Registration Administrative Measures (2020 edition), pharmaceutical products launched in China must obtain a manufacturing permit, making this the primary focus of R&D investment in the pharmaceutical sector. Consequently, indicators such as patent applications or academic publications fail to effectively capture R&D innovation outputs. While New Molecular Entities (NMEs) partially reflect innovation, their share in China remains below 5%, limiting their reliability as an innovation indicator in China.

2.3.2. Evaluation of Financial Efficiency in Pharmaceutical Enterprises

Financial performance is also a key indicator used by scholars to evaluate the operational efficiency of enterprises. Cai and Sun (2013) [59] combined DEA and SFA methods and found that an increase in the stock of technological knowledge significantly enhances a company's revenue. Chen et al. (2015), using a combination of Slack-Based Measure (SBM) and the adjusted residual income model, arrived at similar conclusions. Xia et al. (2022) [60], employing BCC-DEA, analyzed the operational efficiency of Chinese listed pharmaceutical companies and found an overall downward trend in financial efficiency, with only the biopharmaceutical industry showing an upward trend, while the chemical and traditional Chinese medicine industries exhibited declining efficiency. Moreover, Lin et al. (2021) [61], using a two-stage network DEA and Malmquist index, observed that government subsidies had no significant impact on financial efficiency. Yang (2024) [62], applying a three-stage DEA and Malmquist index, revealed that the overall efficiency of Chinese pharmaceutical enterprises is low, with significant fluctuations across the years.

Compared to China, international studies use a broader range of indicators. Gascón et al. (2017) [26] combined financial and innovation indicators to study the efficiency of large pharmaceutical companies in the U.S., revealing that the pharmaceutical industry is highly competitive, as the efficiency gap between efficient and inefficient decision-making units (DMUs) is small. Hamad and Tarnoczi (2021) [63] applied the value-added intellectual capital model to assess the operational efficiency of pharmaceutical companies in the Visegrad countries, including the Czech Republic, Hungary, Poland, and Slovakia, identifying Slovakia as the leader in Human Capital Efficiency (HCE), Structural Capital Efficiency (SCE), and overall Intellectual Capital Efficiency (ICE). Similarly, Riaz et al. (2023) [64] using DEA with outputs such as revenue, Earnings Per Share (EPS), Dividends Per Share (DPS), and Return on Equity (ROE), evaluated the efficiency of pharmaceutical companies in Pakistan.

Additionally, researchers have extended their focus to other dimensions, such as the efficiency of social responsibility and green economics of pharmaceutical enterprises [65]. These studies deepen the understanding of efficiency in the pharmaceutical companies and provide new directions for future research.

In summary, studies on the efficiency of Chinese pharmaceutical enterprises typically focus separately on innovation efficiency and financial efficiency. While environmental efficiency has been explored in other sectors, a significant research gap exists in the integration of financial, innovation, and sustainability dimensions within the operational efficiency evaluation of Chinese pharmaceutical enterprises. Furthermore, current innovation indicators do not fully align with the unique characteristics of Chinese pharmaceutical enterprises. Therefore, research that addresses this gap and incorporates more adaptive indicators is both necessary and meaningful.

3. Materials and Methods

3.1. Data Collection and Software

Sample Scope

The sample includes pharmaceutical enterprises listed on the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE).

Ownership Structure

All the companies are Chinese-listed companies and controlled by Chinese firms.

Time of the Data

Except for the manufacturing permits, all data were from 2022. The number of manufacturing permits was sourced from 2023, as the approval process typically takes about one year after the application is submitted (data from NMPA).

Sample Selection

Companies with long-term losses and those under special treatment (ST) were excluded to ensure the analysis focused on financially viable firms and avoided distortions caused by financial distress. DMUs with missing wastewater emission data were removed to maintain data consistency and ensure the accuracy of environmental efficiency evaluations.

Data Processing

All data were processed to ensure non-negativity.

Industry Classification

The DMUs belong to the C27 category in the ShenWan Industry Classification, representing the pharmaceutical manufacturing industry.

Data Sources

Financial data of DMUs were obtained from the Wind Financial Terminal database, available at https://www.wind.com.cn.

Waste emissions data (bad output) were obtained from the Institute of Public and Environmental Affairs (IPE), accessible at http://www.ipe.org.cn.

Environmental data were obtained from the China Statistical Yearbook, accessible at https://www.stats.gov.cn.

Number of manufacturing permits were from the official website of the NMPA at https://www.nmpa.gov.cn.

Sample Size

A total of 244 samples (DMUs) were obtained.

Software in this Study

The Software for DEA is DEA-Solver 13C and the software for SFA is Frontier 4.1, and both of the software applications are free versions.

3.2. Input Indicators

This study constructs an input indicator system across four dimensions: total assets, operational costs, number of employees, and R&D investment [26,61].

Total Assets (X1)

Total assets represent an enterprise's resource base and capital stock, reflecting its scale and level of capital investment. They serve as a critical input indicator to measure the firm's production capacity.

Operational Costs (X2)

Operational costs refer to the financial investments made during the production process, including expenditures on raw materials, energy consumption, and production management. This indicator captures the scale of production inputs and the efficiency of capital utilization.

Number of employees (X3)

Total employees represent the labor input of the enterprise, reflecting the scale of human resources utilized in the production process.

R&D Investment (X4)

R&D investment measures the financial commitment towards technological innovation and long-term development, reflecting the firm's emphasis on fostering innovation capability and enhancing future competitiveness.

3.3. Output Indicator

Based on a comprehensive review of the literature and the characteristics of the pharmaceutical industry, this study identifies five output indicators: three financial indicators (operating revenue, operating profit, and operating net cash flow), one innovation indicator (manufacturing permits), and one sustainability indicator (pollution equivalent).

Operating Revenue (Y1): Market Performance

Operating revenue reflects the enterprise's market scale and ability to maintain stable operations. It serves as a key indicator of market performance, capturing the firm's efficiency in expanding market share and sustaining growth [26].

Operating Profit (Y2): Profitability

Operating profit indicates the company's profitability and resource utilization efficiency. It directly measures the firm's financial performance, aligning with the objective of evaluating profitability as a dimension of operational efficiency [26].

Operating Net Cash Flow (Y3): Financial Risk Control

Operating net cash flow represents the firm's capacity to manage financial risks and maintain liquidity. This indicator reflects the company's ability to navigate market uncertainties and ensure sustainable financial health, which is essential for assessing risk control capabilities [66].

Manufacturing Permits (Y4): Innovation Capability

Based on the use of NME manufacturing permits as an indicator of innovation output by Gascón, F., J. Lozano (2017) [26] and Schuhmacher, A. (2021) [57], and considering the general patterns of innovation in the sample, this study adopts NMPA-approved manufacturing permits as the measure of innovation output. It captures the firm's success in new product development, including the new drug and generic drug, reflecting its innovation capability.

Pollution Equivalent (Y5, undesirable output): Sustainability

The pollution equivalent serves as an undesirable output indicator, comprehensively evaluating the pollution generated during production. It measures the firm's environmental sustainability performance, reflecting its efficiency in achieving green development goals.

Based on Zhao and Wu (2024) [67], Zhou and Xu (2019) [68], Li (2021) [69], and the Environmental Protection Tax Law of China, this study consolidates undesirable outputs such as COD (Chemical Oxygen Demand), ammonia nitrogen, total phosphorus, and others into a single indicator, pollution equivalent, which is calculated using the following formula:

$$\text{Pollution Equivalent } = \sum_{i=1}^{n} (C_i / F_i) \tag{1}$$

C_i (pollutant emission), represents the amount or concentration of i-th pollutants emitted by a DMU, typically expressed in appropriate units such as tonnes, or kilograms.

F_i (equivalent factor), represents the equivalent factor of the i-th pollutant, which measures its relative harmfulness compared to a reference pollutant. F_i is a non-negative, non-zero number; the smaller the value of F_i, the greater the level of pollution.

3.4. Environmental Variables

According to Michael Porter's theory of regional economic clusters, firms located in specific industry cluster regions can benefit from shared resources, infrastructure, and specialized skills, thereby enhancing their competitiveness and efficiency. Understanding the regional and industrial context is crucial when assessing a company's operational efficiency, as these clusters are external to the firm, yet they can influence its efficiency. Additionally, local macroeconomic factors, such as industry policies, market structures, labor supply, and the level of infrastructure development, can impact the firm's efficiency. Based on this, the study identifies 10 environmental variables influencing operational efficiency, alongside all input and output indicators, as presented in Table 1.

This study consists of three stages.

In the first stage, the undesirable output DEA is employed to obtain the initial efficiency and input slacks.

The second stage involves using SFA to reveal the impact of environmental factors on efficiency, which is referred to as objective two of the study, to further obtain adjusted input variables.

Table 1. Input, output, and environment variables in the study.

Variable Type	Measurement Dimension	Variable Name	Unit
Input Variables	Capital	Input 1: Total assets	Million CNY
	Operation cost	Input 2: Main business costs	Million CNY
	Labor	Input 3: Number of employees	Person
	Emphasis on R&D	Input 4: Investments in R&D	Million CNY
Output Variables	Market Dimensions	Output 1: Operating Revenue	Million CNY
	Profitability	Output 2: Operating Profit	Million CNY
	Risk control capability	Output 3: Operating Cash Flow	Million CNY
	Innovation capability	Output 4: Manufacturing Permits	Units
	Sustainability	Output 5 (undesirable output): Pollutant Equivalent *	Tonne

Table 1. *Cont.*

Variable Type	Measurement Dimension	Variable Name	Unit
Environmental Variables	Economic Scale	Z1: Local Total Gross Domestic Product (GDP)	Billion CNY
	Wealth Level	Z2: Disposable Income	K, CNY/Y
	Innovation Support	Z3: Investment in S&T	100 Million CNY
	Educational Support	Z4: Investment in Science and Technology (S&T)	100 Million CNY
	Labor Supply	Z5: Working-age Labor Force	Million Person
	Tech Transfer Abilities	Z6: Sale of New Product	Billion CNY
	R&D Workforce	Z7: Master and Higher people	Thousand Person
	Ecological Environment Quality	Z8: Treatment Amount of Wastes	Million Tonne
	Openness	Z9: Foreign Investment	100 Million USD
	Cost Structure	Z4: Change Rate of Producer Price Index (PPI)	%

* This value was obtained from Equation (1). For example, if a company emitted the following pollutants in 2022: 1 tonne of COD (F = 1), 1 tonne of total phosphorus (F = 0.25), and 1 tonof petroleum (F = 0.1); therefore, the company's pollution equivalent value for 2022 would be calculated as follows: Pollution Equivalent = (1/1) + (1/0.25) + (1/0.1) = 15 tonnes. In this study, the values of F are based on the Environmental Protection Tax Law of China (can be obtained from https://www.mee.gov.cn).

Finally, the adjusted inputs and original outputs are applied to the undesirable output DEA to achieve the final efficiency, which corresponds to the study's first objective. Figure 1 illustrates the conceptual framework of the study.

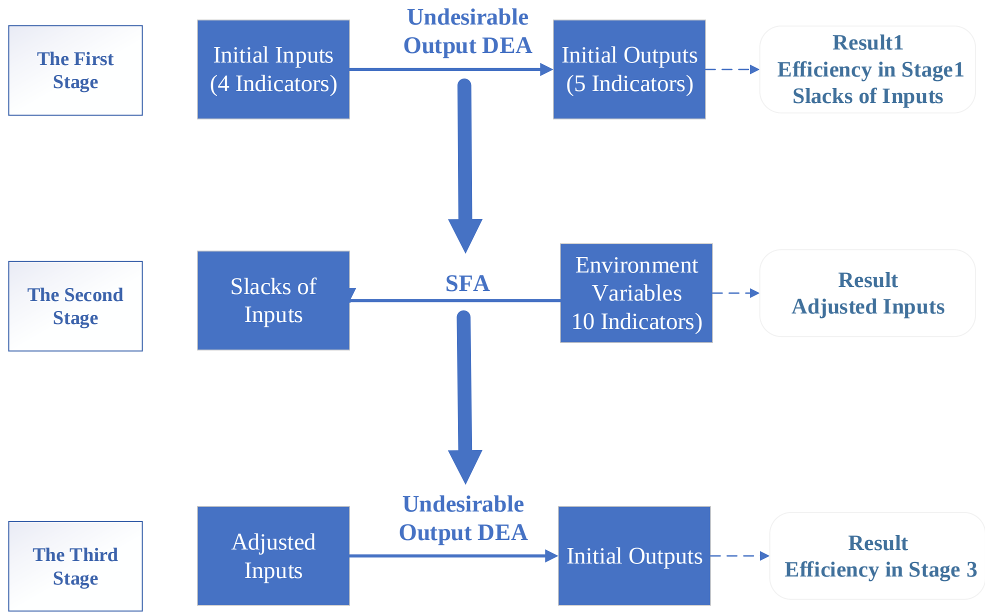

Figure 1. The conceptual framework of this study.

3.5. Methodology

3.5.1. Stage 1: Undesirable Output DEA

In the pharmaceutical industry, materials mainly consist of chemical substances, such as key starting materials, excipients, solvents, and catalysts. Through a series of complex chemical reactions, these materials are gradually transformed into target products, such as APIs. However, due to the incomplete nature of chemical reactions and the complexity of post-reaction processing, multiple undesirable outputs are generated along with the target product. These undesirable outputs include not only by-products but also polluted solvents, wastewater containing chemical substances, solid waste, and volatile organic compounds (VOCs). These outputs are unavoidable in pharmaceutical processes, posing significant challenges for both environmental protection and operational management.

Several approaches are commonly used to handle undesirable outputs in DEA methods. The most straightforward approach is to disregard undesirable outputs, assuming they accompany desirable outputs [40]. The reciprocal transformation method treats undesirable outputs as the reciprocals of "pseudo-inputs", thereby positively correlating them with desirable outputs [42]. However, this approach does not align well with the economic nature of production, making interpretation difficult. Next, the hyperbolic transformation method uses mathematical transformations to handle undesirable outputs, but its theoretical support is limited and lacks clear economic explanations [70]. The linear transformation method treats undesirable outputs as desirable outputs in the DEA model, which, while flexible, is complex and computationally demanding. Additionally, the directional distance function method sets direction vectors to handle desirable and undesirable outputs jointly, making it widely applicable but challenging in terms of direction vector selection and slack variable handling [43].

In this study, we propose to employ a DEA model with undesirable outputs. The DEA model with undesirable outputs evaluates overall efficiency by incorporating multiple inputs, desirable outputs, and undesirable outputs within a unified framework. This model effectively measures the impact of undesirable outputs, such as pollutants, on a firm's efficiency during the production process [44].

Let us decompose the output matrix Y into (Y^g and Y^b, where Y^g and Y^b denote good (desirable) and bad (undesirable) output matrices, respectively. x, y^g, y^b are non-zero and non-negative.

For a DMU, the production possibility set is defined as shown in Equation (2):

$$P = \left\{ \left(x, y^g, y^b \right) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, L \leq e\lambda \leq U, \lambda \geq 0 \right\} \tag{2}$$

where λ is the intensity vector, and L and U are the lower and upper bounds of the intensity vector, respectively. We define the efficiency status in this framework as follows.

Efficient DMU: A DMU (x_0, y_0^g, y_0^b) is efficient in the presence of bad outputs, if there is no vector $(x_0, y^g, y^b) \in P$, such that $x_0 \geq x, y_0^g \leq y^g, y_0^b \geq y^b$ with that at least one strict inequality. In accordance with this definition, the SBM of Tone (2001) [44] can be modified as shown in Equation (3). The Equation (3) defines the efficiency of a DMU in the presence of good and bad outputs, where the production possibility set satisfies at least one strict inequality.

$$\begin{gathered}
\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}}}{1 + \frac{1}{s}\left(W_1 \sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + W_2 \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b} \right)} \\
\text{subject to:} \\
x_o = X\lambda + s^- \\
y_o^g = Y\lambda - s^g \\
y_o^b = Y\lambda + s^b \\
L \leq e\lambda \leq U \\
s^-, s^g, s^b, \lambda \geq 0.
\end{gathered} \tag{3}$$

The s^- and s^b represent excesses in inputs and bad outputs, respectively, while s^g indicates shortages in good outputs. s_1 and s_2 denote the number of elements in s^b and s^g, respectively, and $s = s_1 + s_1$.

Let an optimal solution of the above program be $(\rho^*, s^{-^*}, s^{g^*}, s^{b^*})$, then we can demonstrate that the DMU (x_0, y_0^g, y_0^b) is efficient in the presence of undesirable outputs if and only if $\rho^* = 1, s^{-^*} = 0, s^{g^*} = 0, s^{b^*} = 0$. If the DMU is inefficient, $\rho^* < 1$, it can be improved and become efficient by deleting the excesses in inputs and bad outputs and augmenting the shortfalls in good outputs by the following projection, as shown in Equation (4).

$$\begin{gathered} x_o \Leftarrow x_o - s^{-*} \\ y_o^g \Leftarrow y_o^g + s^{g^*} \\ y_o^b \Leftarrow y_o^b - s^{b^*} \end{gathered} \tag{4}$$

Equation (3) represents the fractional program, which can be transformed into an equivalent linear program using the Charnes–Cooper transformation. By considering the dual side of the linear program, the dual program of Equation (3) can be obtained, as shown in Equation (5), with u^g, u^b for the Constant Returns to Scale (CRS) case, where $L = 0$ and $U = \infty$ [44].

$$\begin{gathered} \max \mathrm{u}^g\, y_o^g - vx_o - u^b y_o^b \\ \text{subject to} \\ u^g Y^g - vX - u^b Y^b \leq 0 \\ v \geq \tfrac{1}{m}[1/x_o] \\ u^g \geq \tfrac{1+u^g y_o^g - vx_o - u^b y_o^b}{s}\left[1/y_o^g\right] \\ u^b \geq \tfrac{1+u^g y_o^g - vx_o - u^b y_o^b}{s}\left[1/y_o^b\right] \end{gathered} \tag{5}$$

The dual variables v and u^b can be interpreted as the virtual price of inputs and bad outputs, and the ug can be interpreted as the good output price. The above dual program aims at obtaining the optimal virtual costs for the DMU so that the profit $u^g y^g - vx - u^b y^b$ does not exceed zero for every DUM and maximizes the profit $u^g y_0^g - vx_0 - u^b y_0^b$ for the DMU concerned. Apparently, the optimal profit is at best zero, and this identifies the DMU as efficient.

In the undesired output model, the weights for desirable and undesirable outputs need to be assigned based on the researcher's judgment regarding the relative importance of each. Let W_1 and W_2 represent the weights for desirable and undesirable outputs, respectively, where $W_1 > 0$, $W_1 > 0$ and $W_1 + W_2 = 1$. Therefore, in consideration of desirable and undesirable outputs, the objective function can be modified, transforming Equation (3) into Equation (6).

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}}}{1 + \frac{1}{s}\left(W_1 \sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + W_2 \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b}\right)} \tag{6}$$

In this study, there are five outputs in total: four desirable outputs and one undesirable output. To balance the importance of the outputs, the total weight for the desirable outputs is set to 0.8, reflecting their significance in evaluating performance. The weight for the undesirable output is set to 0.2, emphasizing its impact on efficiency without overwhelming the overall assessment. This weighting scheme ensures a comprehensive evaluation that aligns with the study's objectives.

3.5.2. Stage 2: The SFA Model

Based on the Theory of Industrial Agglomeration and the Theory of Regional Economic Clusters, related industries and supporting relationships among enterprises, as well as factors like labor, innovation, and infrastructure within specific regions, can significantly influence firms' operational efficiency. At the same time, random errors are unavoidable. The combined effects of environmental factors and random disturbances may lead to bias in efficiency evaluation results.

To address this, the second stage of this study employs SFA to reveal the impact of environmental factors and random errors on efficiency. By calculating and eliminating these influences, the study places all DMUs under equitable environmental conditions and random disturbances, ensuring fairness and accuracy in efficiency assessment.

The SFA model decomposes input slacks into management factors, environmental factors, and random factors, thereby identifying the sources of inefficiency through regression.

First, the input slack variables are defined as follows:

$$S_{ij} = x_{ij} - \sum \lambda_{ij} \chi_{ij} \tag{7}$$

Equation (7) defines the input slack variables, where S_{ij} represents the input slack of the i-th input factor in j-th DMU, λ_{ij} and χ_{ij} denote the optimal combination of inputs for the j-th DMU, while x_{ij} represents the actual input amount for the i-th input factor in the j-th DMU.

Following the input slack defined in Equation (7), Equation (8) further decomposes it into three components: environmental factors, management inefficiency, and random error.

$$S_{ij} = f\left(Z_j, \beta_i\right) + v_{ij} + \mu_{ij}, j = 1, 2, \cdots, M; i = 1, 2, \cdots, N \tag{8}$$

Among them, S_{ij} represents the i-th input factor for the j-th DMU. Z_j represents the environmental variables in the j-th DMU, and β_i represents their corresponding coefficients. Thus, $f(Z_j, \beta_i)$ indicates the impact of environmental factors on input slack variables, which are generally assumed that $f(Z_j, \beta_i) = Z_j\beta_i$, and $v_{ij} + \mu_{ij}$ represents the composite error term (ε_{ij}), which includes the random error term (v_{ij}) and management inefficiency term (μ_{ij}). The random error v_{ij} follows a symmetric normal distribution $N(0, \sigma_v^2)$, representing statistical noise, while μ_{ij} follows a non-negative truncated normal distribution $N^+(0, \sigma_u^2)$ accounting for inefficiency effects.

Before adjusting the input factors, it is necessary to separate the random disturbance term from the composite error term and the management inefficiency.

Based on the distribution for managerial inefficiency, it is can be separated by the process from Equation (9) to Equation (14):

$$\varepsilon = S_{ij} - f\left(Z_j, \beta_i\right) \tag{9}$$

$$\sigma_\mu = \sqrt{(\gamma * \sigma^2)} \tag{10}$$

$$\sigma_v = \sqrt{\sigma^2 - \sigma_\mu^2} \tag{11}$$

$$\sigma^* = \left(\sigma_\mu * \sigma_v\right)/\sigma \tag{12}$$

$$\lambda = \sigma\mu/\sigma v \tag{13}$$

$$E(\mu \mid \varepsilon) = \sigma^* * \left[\frac{\phi\left(\lambda\frac{\varepsilon}{\sigma}\right)}{\Phi\left(\frac{\lambda\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma}\right] \tag{14}$$

In this process, Equation (9) calculates the mixed error term, while Equations (10) and (11) obtain standard deviations of management inefficiency and random error, respectively. The standard deviation of the composite error is obtained from Equation (12). Furthermore, Equation (13) calculates the bias coefficient, which measures the relationship between management inefficiency and random error terms. Finally, Equation (14) computes the management inefficiency term under the assumed distribution.

The random error term can be calculated using the Equation (15).

$$v_{ij} = S_{ij} - Z_j\widehat{\beta}_i - \widehat{E}\left(v_{ij} \mid v_{ni} + \mu_{ij}\right), \quad j = 1, 2, \cdots, M; i = 1, 2, \cdots, N \tag{15}$$

Finally, the readjusted inputs can be obtained as follows:

$$\widehat{x_{ij}} = x_{ij} + \left[\max_{n}\left\{Z_j\widehat{\beta_i}\right\} - Z_j\widehat{\beta_i}\right] + \left[\max_{n}\left\{\widehat{v_{ij}}\right\} - v_{ij}\right] \tag{16}$$

In Equation (16), ($\widehat{x_{ij}}$) represents the adjusted input factors, ($\widehat{\beta_i}$) represents the estimated coefficients of the external environmental variables, and v_{ij} represents the estimated values of the random disturbance term.

3.5.3. Recalculate by the Model in Stage 1 with the Adjusted Input

Bring the adjusted input and original output variables back into the undesirable output DEA of Stage 2, and recalculate the efficiency results after adjustment.

The detailed calculation process of the SFA has been uploaded and is available in the data availability section at the end of the paper.

4. Results

4.1. Stage 1 and Stage 3 Result: Undesirable Output DEA Results

In the first stage, the undesirable output model in DEA-Solver 13C was employed to evaluate the operational efficiency of 244 pharmaceutical enterprises in China. Without accounting for environmental impacts and random disturbances, three types of efficiency were assessed: technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE).

Table 2 presents the results for different regions in both the first and third stages. The results indicate that among the 244 decision-making units (DMUs), 47 were identified as technically efficient, representing 19.26% of the total sample. The average TE was 0.352, the average PTE was 0.388, and the average SE was 0.88, reflecting a generally low level of efficiency accompanied by significant regional disparities. The standard deviations for TE, PTE, and SE were 0.371, 0.385, and 0.201, respectively, further highlighting the variability in efficiency distribution across DMUs.

Notably, Inner Mongolia exhibited zero efficiency in both TE and PTE. Additionally, provinces such as Shaanxi, Fujian, and Hainan, along with Tianjin, demonstrated relatively low TE scores. These findings suggest that, while certain provinces exhibit high efficiency in pharmaceutical enterprises, the overall efficiency remains low, with substantial regional variations. These discrepancies in efficiency may be attributed to factors such as resource allocation, policy support, and the varying levels of economic development across provinces. This analysis provides a foundation for further investigation into the environmental and inefficiency factors in subsequent stages.

The results of Stage 1 and Stage 3 by undesirable output DEA are listed in Table 2.

Table 2. The result of Stage 1 and Stage 3.

Region		The Efficiency in Stage 1			The Efficiency in Stage 3		
		CRS	VRS	SE	CRS	VRS	SE
Nation Wide	Average	0.352	0.388	0.880	0.387	0.423	0.903
	SD	0.371	0.385	0.201	0.371	0.387	0.208
	Efficient DMUs		47, (19.26%)			45, (18.44%)	
North China	Beijing	0.324	0.353	0.903	0.465	0.516	0.890
	Tianjin	0.161	0.185	0.671	0.180	0.196	0.820
	Hebei	0.393	0.429	0.928	0.473	0.709	0.743
	Shanxi	0.278	0.447	0.799	0.319	0.498	0.807
	Inner Mongolia	0.000	0.000	0.919	0.000	0.000	0.978

Table 2. *Cont.*

Region		The Efficiency in Stage 1			The Efficiency in Stage 3		
		CRS	VRS	SE	CRS	VRS	SE
Northeast China	Liaoning	0.443	0.478	0.929	0.534	0.549	0.971
	Jilin	0.532	0.540	0.943	0.410	0.540	0.864
	Heilongjiang	0.857	0.863	0.980	0.711	0.750	0.943
East China	Shanghai	0.403	0.407	0.898	0.704	0.714	0.938
	Jiangsu	0.317	0.395	0.834	0.355	0.383	0.943
	Zhejiang	0.294	0.321	0.853	0.337	0.363	0.860
	Anhui	0.308	0.316	0.858	0.251	0.265	0.966
	Jiangxi	0.482	0.484	0.939	0.431	0.512	0.877
	Fujian	0.200	0.200	0.938	0.129	0.131	0.963
	Shandong	0.468	0.541	0.856	0.361	0.397	0.887
Central China	Henan	0.237	0.240	0.951	0.258	0.260	0.966
	Hubei	0.330	0.341	0.834	0.330	0.352	0.869
	Hunan	0.319	0.436	0.821	0.329	0.469	0.828
South China	Guangdong	0.233	0.254	0.901	0.480	0.501	0.900
	Guangxi	0.043	0.044	0.906	0.047	0.048	0.973
	Hainan	0.211	0.219	0.937	0.248	0.251	0.984
Southwest China	Chongqing	0.616	0.649	0.916	0.556	0.571	0.946
	Sichuan	0.398	0.411	0.906	0.428	0.433	0.968
	Guizhou	0.596	0.657	0.905	0.127	0.159	0.897
	Yunnan	0.619	0.623	0.948	0.315	0.330	0.933
	Tibet	0.535	0.652	0.870	0.477	0.495	0.917
Northwest China	Shaanxi	0.190	0.193	0.965	0.107	0.107	0.988
	Gansu	0.613	0.613	1.000	0.075	0.075	0.997

CRS = Constant Returns to Scale assumption; VRS = Variable Returns to Scale (VRS) assumption; SE = Scale efficiency

In summary, under the current environment, pharmaceutical companies in China exhibit low efficiency and uneven distribution, likely influenced by local environmental factors, necessitating further research to explore the impact of the environment on efficiency.

4.2. SFA Stage Results

In Stage 2, SFA regression was employed to analyze the relationship between the input slacks obtained in Stage 1 and the operational environment, revealing the impact of environmental factors on the efficiency. Additionally, the input variables were adjusted to provide a foundation for Stage 3.

A total of ten independent variables were selected for the regression, representing various aspects, including regional economic development level, wealth level of local residents, local investment in technology, local investment in education, supply of working-age labor, level of new technology conversion, availability of high-level talent, local ecological environment, openness to foreign investment, and the industrial price environment.

Table 3 presents the impact of ten environmental factors on input slacks in the SFA regression. As shown in Table 3, the likelihood ratio (LR) test values for the four input slack variables exceed the threshold of the mixed chi-square distribution test and are significant at the 1% confidence level, indicating the validity of the model. The γ values close to 1 indicate that input slack is primarily attributable to managerial inefficiency rather than statistical noise, suggesting that enterprises can improve operational efficiency through managerial analysis and optimization of input slacks.

As shown in Table 3, environmental variables have varying impacts on different types of input slacks, and environmental variables also have varying impacts on different types of redundancy.

Table 3. Results of SFA regression on the impact of environmental factors on input slacks.

Independent Variable		Dependent Variable			
		Slack of Total Asset	Slack of Operation Cost	Slack of Number of Employees	Slack of R&D Investment
Constant Term		−3858.65	−213.93	−1594.92	−362.41
Z1	$\beta 1$ t-ratio	−0.236 −0.671	0.000 0.006	−0.056 −3.328 ***	0.032 4.304 ***
Z2	$\beta 2$ t-ratio	44.364 44.408 ***	1.836 5.971 ***	33.384 10.161 ***	5.148 7.455 ***
Z3	$\beta 3$ t-ratio	2.390 2.455 **	0.099 0.632	0.523 5.120 ***	0.011 0.062
Z4	$\beta 4$ t-ratio	−47.110 −47.110 ***	−12.349 −18.543 ***	−51.077 −50.732 ***	3.716 3.716 ***
Z5	$\beta 5$ t-ratio	52.719 52.721 ***	4.489 1.222	35.950 23.418 ***	−0.200 −0.195
Z6	$\beta 6$ t-ratio	−0.081 −0.103	−0.001 −0.017	−0.137 −2.250 **	−0.058 −3.475
Z7	$\beta 7$ t-ratio	−0.643 −0.768	0.042 0.561	−0.745 −2.371 **	−0.111 −1.955
Z8	$\beta 8$ t-ratio	2.578 2.585 **	0.226 3.258 ***	2.439 9.503 ***	0.266 1.883
Z9	$\beta 9$ t-ratio	0.109 0.154	0.013 0.290	0.151 1.683	−0.024 −1.727
Z10	$\beta 10$ t-ratio	6.534 6.534 **	2.064 2.069 **	−82.265 −67.977 ***	−1.750 −1.748
σ^2		15,462,467	176,757	6,368,072	105,940
γ		0.999	0.999	0.999	0.999
LR test of the one-sided error		143.78	187.36	187.11	199.85

Note: **, *** indicate significance at the 5%, and 1% levels

Impact of Environmental Factors on Asset Redundancy

Investment in education reduces asset redundancy, while factors such as income levels, technological investments, and waste emissions generally increase asset redundancy.

Impact of Environmental Factors on Operational Cost Redundancy

Income levels, pollutant emissions, and price levels have an adverse effect on operational cost, whereas education investment helps to reduce operational cost redundancy.

Impact of Environmental Factors on Employee Redundancy

Income levels, pollutant emissions, and labor supply increase employee number, while technological conversion efficiency, local economic development, education investment, and price levels help reduce employee redundancy.

Impact of Environmental Factors on R&D Investment Redundancy

Local economy, income levels, and education investment increase R&D investment, while high-level talent reduces R&D investment.

In the following step, the adjusted input values can be calculated using Equation (9) to Equation (16).

In summary, the SFA reveals the impact of environmental factors on efficiency. Investment in education enhances efficiency, while local pollutant emissions and per capita income levels reduce it.

4.3. The Operation Efficiency Revaluation in Stage 3

In Stage 3, to measure the final, most accurate efficiency, the undesirable output DEA was employed with the adjusted input and initial outputs in CRS and VRS and all of the results are listed in Table 2. This final evaluation places all DMUs at the same level of environment and luck. Therefore, the results more accurately reflect the actual operational efficiency of the DMUs, as the influence of environmental factors and statistical noise has been removed in the second stage.

Table 3 presents the changes in TE and pure technical efficiency (PTE) of pharmaceutical enterprises across 28 provinces before and after adjustment by SFA. Following SFA adjustments, the mean values of TE, PTE, and SE shifted from 0.352, 0.388, and 0.880 to 0.387, 0.423, and 0.903, respectively, with the number of efficient DMUs decreasing from 47 to 45, representing proportions of 19.26% and 18.44%. After the adjustment by SFA in Stage 2, which removes the influence of environmental factors, the significant changes in efficiency and its regional distribution indicate the substantial impact of the environment on efficiency.

However, both pre-adjustment and post-adjustment results indicate that overall efficiency remains relatively low, with a modest proportion of efficient DMUs highlighting significant regional disparities and reflecting considerable differences in operational efficiency among pharmaceutical enterprises across provinces.

Notably, prior to removing the effects of environmental factors and statistical noise, the highest TE and PTE scores were observed in Heilongjiang, Yunnan, Chongqing, and Gansu, with values of 0.857, 0.619, 0.616, and 0.613, respectively. Except for Chongqing, the overall economic performance of these provinces is not particularly prominent. This result may be attributed to the inclusion of environmental emissions as undesirable outputs in this study, as well as the use of manufacturing permits as key output indicators, which provides a more comprehensive evaluation of enterprise productivity. In contrast, Inner Mongolia recorded the lowest efficiency scores, which aligns with expectations given the relatively underdeveloped foundation of its pharmaceutical industry.

In summary, the results highlight the substantial impact of environmental factors on efficiency, with significant regional disparities persisting even after adjustments, and a relatively low overall efficiency across pharmaceutical enterprises in China.

5. Discussion

According to the results, this chapter discusses the changes in TE and PTE and their potential causes. It analyses the impact of environmental factors on efficiency and compares the findings of this study with existing research.

5.1. Technical Efficiency Discussion

The comparison between Stage 1 and Stage 3 reveals that excluding environmental factors significantly impacted the efficiency rankings of enterprises. A total of 59 DMUs experienced a decline in efficiency in Stage 3, accounting for 24.2% of all DMUs, with 19 previously DEA-efficient DMUs becoming inefficient. This suggests that the efficiency of these DMUs in Stage 1 was overestimated. The relatively high efficiency of these enterprises was not due to superior management performance but more favorable environmental conditions, such as low waste treatment costs, timely waste management, or relatively low labor costs.

Conversely, 157 DMUs, accounting for 64.3%, showed improved efficiency, with 17 DMUs becoming DEA-efficient in Stage 3. This indicates that the efficiency of most enterprises was underestimated in Stage 1 due to unfavorable environmental conditions that negatively affected their performance.

The remaining 28 DMUs did not experience any change in efficiency, suggesting that the environmental conditions in their regions had little to no impact on their operational efficiency.

Figure 2 presents the results of the comparison in TE across different regions between Stage 1 and Stage 3.

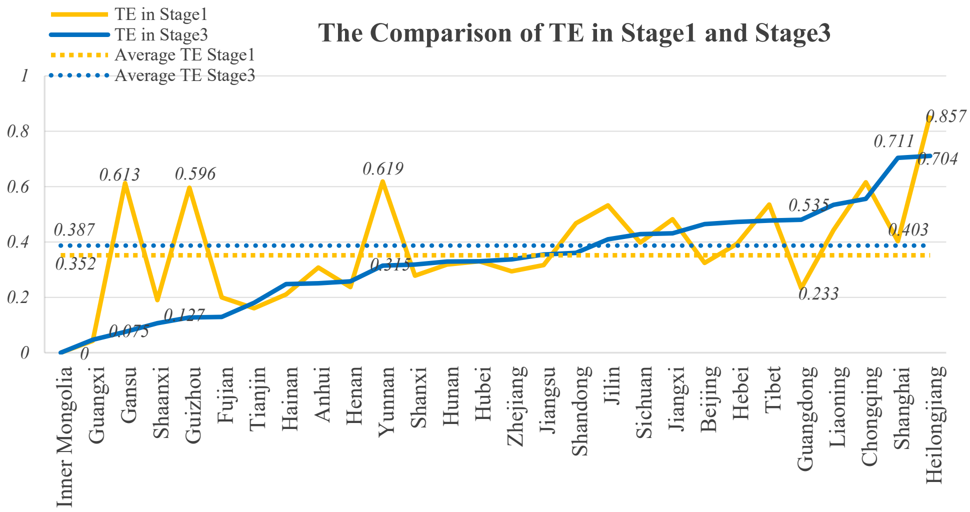

Figure 2. The comparison of TE in different regions in Stage 1 and Stage 3.

After excluding environmental factors in Stage 2 using SFA, a comparison of the TE changes across regions between Stage 1 and Stage 3 reveals the following findings:

Firstly, after the adjustment, Heilongjiang, Shanghai, Chongqing, and Liaoning achieved the highest technical efficiency scores, indicating that pharmaceutical enterprises in these regions exhibit significant operational advantages. This can be attributed to the robust industrial foundations established during the early stages of pharmaceutical development in Heilongjiang and Liaoning, along with relatively low labor costs. Similarly, Shanghai and Chongqing leverage their advanced pharmaceutical industrial bases and abundant talent resources to attain high operational efficiency. These adjustments provide a more accurate reflection of the intrinsic operational performance in these regions.

Secondly, TE declined in 12 regions during Stage 3, most of which are economically less developed areas, including Gansu, Guizhou, and Yunnan, where the decline was most significant. This suggests that the efficiency levels in Stage 1 may have been overestimated due to favorable environmental conditions, such as low labor costs and manageable waste treatment expenses. Post-adjustment, the actual underlying efficiency of these regions has been revealed.

Thirdly, efficiency improved in 14 provinces after adjustments, with Beijing, Shanghai, and Guangdong showing the most significant increases. Notably, regions exhibiting the most remarkable efficiency improvements are predominantly economically developed areas. This indicates that current environmental conditions, such as high labor costs and stringent pollution control regulations, impose considerable operational pressures on pharmaceutical enterprises in these regions, thereby constraining their efficiency. The post-adjustment results provide a more precise representation of their intrinsic efficiency.

Furthermore, Inner Mongolia, Guangxi, and Shanxi consistently demonstrated low efficiency in the first and third stages, with minimal changes after adjustments by SFA. This indicates that the pharmaceutical industrial infrastructure in these provinces remains underdeveloped, significantly constraining the pharmaceutical industry. Additionally, these regions lack favorable environmental conditions, such as advanced education systems, an adequate supply of high-level talent, policy support, and a well-preserved ecological environment.

5.2. Pure Technical Efficiency Discussion

The comparison between Stage 1 and Stage 3 reveals that environmental factors had a significant impact on PTE rankings. In the VRS model, 56 DMUs were identified as PTE-efficient in Stage 1. However, after accounting for environmental influences, 19 of these 56 DMUs were no longer efficient in Stage 3. Additionally, the average PTE for these 19 DMUs dropped to 0.389 in Stage 3, which is below the overall average. After SFA adjustment, PTE scores declined for 70 DMUs, while 35 remained unchanged. A comparison between the first and third Stages of the DEA analysis shows that, among the 29 provinces, the average pure technical efficiency (PTE) decreased in 11 provinces, with the most significant declines observed in Gansu, Yunnan, and Guizhou, suggesting a potential overestimation of PTE in Stage 1, likely due to favorable environmental conditions.

Conversely, 15 provinces experienced increases in PTE, with the most notable improvements in Shanghai, Hebei, Guangdong, and Beijing. This indicates that these regions may have faced unfavorable environmental conditions that impacted PTE. Consequently, the pure technical efficiency in Stage 1 may have been underestimated in these regions.

Figure 3 illustrates the comparison of PTE across different regions between Stage 1 and Stage 3.

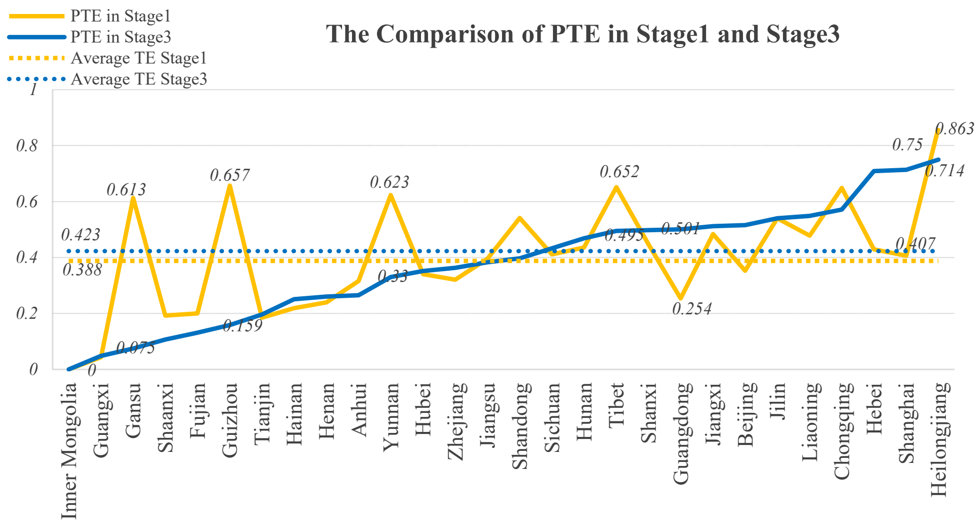

Figure 3. The comparison of PTE in different regions in Stage 1 and Stage 3.

The explain this is similar to the cause TE changes. However, Hebei Province stands out among the underestimated regions due to its unique characteristics, as it is not an economically developed area. A possible explanation lies in Hebei's proximity to Beijing, which has resulted in challenges such as high labor costs, strict EHS policies, significant outflows of high-level talent, and insufficient efforts in talent acquisition and development. This places Hebei alongside Beijing, Shanghai, and Guangdong as a region where environmental factors are unfavorable for pharmaceutical companies.

5.3. The Discussion of Impact of Environmental Factors on Efficiency

The impact of environmental variables on efficiency is both diverse and complex, with certain factors playing a significant role in enhancing efficiency. Investments in local education and the attraction of high-level talent serve as key reasons for fostering innovation capabilities, improving management standards, and increasing operational efficiency. These elements collectively contribute to the overall improvement of efficiency. Furthermore, although regional technological investments may increase excessive input of assets and labor, they do not necessarily result in higher operational costs. Instead, such investments often enhance asset allocation and equipment upgrading, and optimize production processes, thereby replacing outdated production facilities.

However, certain environmental thereby reduce efficiency. This phenomenon arises because high-income regions typically encounter not only increase labor costs but also heightened levels of automation, increased operational expenses, and stricter EHS regulations. To comply with these requirements, companies are compelled to make substantial investments in assets, labor, costs, and R&D. The findings from both the first and third stages underscore these challenges, particularly in economically developed regions such as Beijing, Shanghai, and Guangdong.

Moreover, increasing pollutant emissions significantly reduces efficiency by exacerbating input slacks across total assets, operation costs, number of employees, and R&D investments. Specifically, high waste emissions not only pollute the regional ecological environment but indicate inadequacies in environmental infrastructure. In industrialized regions such as Shanghai and Beijing, the demand for waste treatment frequently exceeds the capacity of existing facilities. Conversely, less developed regions, such as Guangxi and Shanxi, face challenges due to outdated or insufficient waste management systems, a result of weaker industrial foundations. The pharmaceutical industry's waste, characterized by its complex composition and high treatment difficulty, exacerbates these issues. As a result, pharmaceutical enterprises must allocate more resources to waste treatment facilities, operational expenditures, labor, and R&D for developing green processes, thereby reducing operational efficiency.

A summary based on the comparison of DEA results from the first and third stages, combined with the analysis of environmental impacts in the second stage, reveals that the driving factors of efficiency differ across regions. The high efficiency observed in Shanghai and Chongqing can be attributed to education investment and the introduction of high-level talent, which enhances internal management and resource optimization. In contrast, the high efficiency observed in Heilongjiang and Liaoning can primarily be from low labor costs, which help reduce operational expenses improve resource allocation, and increase efficiency and competitiveness. Regions such as Yunnan, Guizhou, and Gansu are particularly suitable for the development of the pharmaceutical industry due to their advantages in labor costs and favorable ecological environments. On the other hand, regions like Beijing, Shanghai, and Guangdong currently face challenges for pharmaceutical industry development due to factors such as high labor costs and insufficient waste treatment capacities. Lastly, low-efficiency regions like Inner Mongolia, Guangxi, and Shanxi suffer primarily due to a weak foundation in the pharmaceutical industry and low technological levels, with environmental factors having relatively minimal influence on their performance.

5.4. Main Findings and Linkage to Existing Research

This study reveals that the overall efficiency of pharmaceutical enterprises in China is relatively low, with significant regional disparities, which aligns with findings from related research on innovation efficiency in China [28,55].

Environmental factors may lead to enterprises being influenced by varying environmental or resource conditions. However, excluding these impacts allows for the true operational efficiency of enterprises to be revealed [71]. In this study, after excluding environmental factors and random disturbances, the efficiency of pharmaceutical enterprises exhibits notable changes, indicating that the current environmental factors significantly influence the efficiencies of the DMUs.

Further analysis indicates that enterprises in developed regions (e.g., Beijing, Shanghai, Guangdong) show significant efficiency improvements after excluding environmental factors. This suggests that the current environment in these regions is not conducive to the development of the pharmaceutical industry. In contrast, less developed regions (e.g., Yunnan, Guizhou, Gansu) demonstrate higher efficiency in the first stage but experience significant declines in Stage 3. This phenomenon aligns with the predictions of the Comparative Advantage Theory, which posits that developed regions, due to their advanced industrialization and limited environmental capacity, are less suitable for supporting high-pollution pharmaceutical enterprises. Conversely, less developed regions with greater environmental capacity are better positioned to accommodate such industries [72–74].

Additionally, China's regional development imbalance and disparities in planning exacerbate these phenomena. According to the Theory of Industrial Agglomeration, high-end industries tend to concentrate in developed regions with high technological and managerial advantages, whereas high-pollution industries, such as the pharmaceutical industry, are more inclined to migrate to less developed regions with looser environmental regulations. Environmental regulations significantly affect industrial efficiency across regions, which also explains why the pharmaceutical industry often finds environmental advantages in economically underdeveloped regions [75–77].

Finally, some enterprises and regions, despite minimal environmental impacts, exhibit low efficiency in both the first and third stage of evaluation. These regions are typically characterized by weak economic and industrial foundations. The main causes of inefficiency include underdeveloped industrial infrastructure, lagging technological innovation, insufficient policy support, and inadequate infrastructure. Furthermore, as a high-pollution industry, the pharmaceutical sector is heavily reliant on path dependency and the coordination of upstream and downstream industries, which also contributes to inefficiency [78,79]. This explains why regions like Inner Mongolia, Shanxi, and Guangxi remain inefficient both in Stage 1 and Stage 3.

This phenomenon is similarly observed in the global pharmaceutical value chain. For instance, countries like the United States, Switzerland, and Germany leverage their technological advantages and well-developed infrastructure to position themselves as high-efficiency core regions within the value chain. In contrast, developing countries such as India, Mexico, and China excel in the production of pharmaceutical intermediates, active pharmaceutical ingredients (APIs), and generic drugs, benefiting from their cost advantages. Meanwhile, countries like Brazil, Russia, and Saudi Arabia exhibit lower levels of value chain integration but hold the potential for further development as pharmaceutical exporters [80–82].

6. Conclusions

6.1. The Main Findings

This study employs a three-stage DEA model incorporating undesirable outputs to comprehensively assess the operational efficiency of Chinese listed pharmaceutical enterprises from the perspectives of finance, innovation, and sustainability. The results indicate that overall efficiency is relatively low, with significant regional disparities. Currently, environmental conditions in developed regions such as Beijing, Shanghai, and Guangdong are relatively unfavorable for operational efficiency, whereas less developed regions such as Yunnan, Guizhou, and Gansu are more favorable. SFA analysis reveals that management inefficiency and environmental factors are the primary drivers of efficiency, while statistical noise has a limited effect. Enhancing education and talent supply contributes to improved regional efficiency, while pollutant emissions significantly suppress corporate efficiency. These findings provide clear implications for enterprise management and policy formulation.

6.2. Implications from the Study for Management

This study provides managerial insights for pharmaceutical enterprises, especially those with low efficiency. Efficiency can be improved in four key areas.

Firstly, for enterprises with high asset redundancy, it is crucial to assess the rationality and necessity of their asset allocation. Additionally, timely utilization or disposal of idle assets should be carried out to improve asset turnover. Large testing equipment, such as Nuclear Magnetic Resonance (NMR) in pharmaceutical companies, often remains underutilized. This can improve the asset turnover ratio by expanding the business to third-party testing services. Companies with excess production capacity can expand the business to Contract Development and Manufacturing Organization services, which can not only improve the asset turnover ratio but also facilitate business transformation.

Furthermore, by adopting lean management strategies, companies can effectively reduce waste in production and operations, leading to higher material utilization. Non-core business activities, such as intermediates, can be considered for global sourcing, for example from India. Active pharmaceutical ingredient (API) production can be outsourced to companies located in regions with favorable environmental conditions, such as Yunnan, Gansu, and Guizhou. For materials with a stable long-term supply, supply chain optimization can be achieved through strategic sourcing or Vendor Warehouse Management Systems (VWMS), which helps improve material turnover efficiency.

Additionally, optimizing organizational structure is crucial for improving collaboration and operational efficiency. In high-income regions such as Shanghai, Beijing, and Guangdong, companies should focus on the application of automation technologies and systems (Distributed Control Systems or Batch Processes), reducing reliance on manpower. In lower-income regions, human resource utilization can be optimized through training, incentives, and organizational restructuring.

Lastly, companies should focus their R&D investments on core technologies and key projects, while avoiding excessive dispersion of resources. This ensures that R&D outcomes can be quickly transformed into market-leading products. For early-stage research, such as drug discovery, industry–academia collaboration can accelerate the process. Non-core activities can be outsourced to enterprises in favorable regions, reducing redundancy in R&D investment.

6.3. Implications from the Study for Policy-Makers

Firstly, local governments should increase the construction of waste treatment facilities to ensure that local enterprises have sufficient waste treatment capacity, while strengthening the supervision of waste discharge. This dual pronged strategy can not only effectively improve the quality of the ecological environment, but also provide more comprehensive waste management support for enterprises, helping them reduce the operational burden caused by environmental issues and thus enhance overall efficiency. For example, in regions like Gansu and Guizhou, local governments can provide special funding support, subsidize enterprises to introduce advanced waste treatment technologies, and promote the construction of regional waste treatment centers to reduce the environmental protection costs of enterprises.

Secondly, local governments should increase investment in the education sector to cultivate and attract high-end technical talents. The demand for professional and technical talents in the pharmaceutical industry is particularly urgent, and the completeness of the local education system and the quality of talent reserves directly affect the innovation ability and operational efficiency of enterprises. By improving education levels and attracting high-end talents, local governments can provide stronger talent support for enterprises and help them achieve efficient development. For example, in areas such as Hubei and

Henan where labor resources are abundant but high-end technical talents are relatively scarce, local governments can collaborate with universities and research institutions to establish specialized courses or talent training programs for pharmaceutical research and development, while providing preferential policies to attract external high-end talents to flow in, further enhancing the technological innovation capabilities of enterprises in the region.

In addition, local governments should formulate differentiated development strategies based on the environmental conditions and economic background of the region. In areas with well-established waste treatment facilities and low labor costs (such as Gansu, Guizhou, Hubei, and Henan), we can actively undertake industrial transfer from developed regions such as Beijing, Shanghai, and Guangdong. This can not only alleviate the pressure of industrial concentration in developed areas, but also promote economic development in underdeveloped areas and achieve a more balanced distribution of industries. For example, local governments can attract pharmaceutical companies from developed regions to relocate some production processes or R&D centers to these areas by providing tax incentives and subsidy policies, while promoting local enterprises to upgrade their technology and extend their industrial chains, thereby enhancing regional competitiveness and promoting coordinated development nationwide.

6.4. The Limitation of the Study

Although this study reveals changes in the efficiency and regional disparities of pharmaceutical companies in China by excluding the environmental factors and random disturbances, there are still some limitations that require further exploration.

Firstly, this study primarily relies on data from listed pharmaceutical companies and does not comprehensively cover the efficiency of non-listed companies and international companies. This data bias may impact the comprehensiveness of the results. Secondly, while the study incorporates a wide range of environmental factors, certain limitations remain, as it does not fully account for all environmental influences, such as the impact of global market conditions (e.g., global price increases of vitamins). These unforeseen fluctuations could affect the results. Additionally, the static analysis method employed in this study fails to reflect the dynamic evolution of corporate efficiency, which may not fully capture the long-term trends and underlying drivers of efficiency changes.

6.5. Future Research

Firstly, the scope of the research can be further expanded by including small and medium-sized enterprises (SMEs), and international companies, exploring the similarities and differences in efficiency changes among enterprises of different sizes and types, as well as their driving factors.

Secondly, dynamic efficiency analysis methods, such as total factor productivity growth models or time series analysis, could be introduced to examine the evolution of enterprise efficiency over different periods, thereby revealing the dynamic characteristics of long-term trends and efficiency changes.

Finally, another method, such as principal component analysis, could be incorporated to provide a more comprehensive explanation of environmental factors.

Through further exploration in these directions, a more comprehensive understanding of the mechanisms driving efficiency changes in pharmaceutical companies can be revealed, providing more targeted guidance for policymakers and business managers.

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