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Assessing Manufacturing Efficiency in Central Plains Cities: A Three-Stage DEA and Malmquist Index Approach

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Abstract: To investigate the high-quality and efficient development of the manufacturing industry in the Central Plains Urban Agglomeration (CPUA), this paper uses the three-stage Data Envelopment Analysis (DEA) and Malmquist index model to evaluate and analyze the manufacturing development efficiency of 30 prefecture-level cities in five provinces of China in the CPUA from 2017 to 2022. First, the DEA model is applied to evaluate the comprehensive efficiency of the manufacturing industry in 30 regions of the CPUA; second, the Stochastic Frontier Analysis (SFA) regression model is used in conjunction with the technical efficiency and scale efficiency of the manufacturing industry to deeply explore and adjust the causes of the current situation in various regions; finally, after re-analyzing the efficiency with the corrected input-output data, the Malmquist index model is used to analyze the total factor productivity index and its decomposed efficiency of the manufacturing industry in the CPUA from 2017 to 2022. The study shows that the pure technical efficiency (PTE) of the 30 prefecture-level cities in the CPUA from 2017 to 2022 is stable and relatively good, and the main reason for the overall low comprehensive efficiency is the poor scale efficiency; after excluding the interference of environmental factors, the average comprehensive efficiency of each city is lower than before the adjustment, with environmental factors and random errors having a significant impact on the manufacturing industry, especially in Bengbu City; the main factor in the decline of the total factor productivity of the manufacturing industry in the CPUA is the hindrance of technological progress; the spatial distribution of the comprehensive efficiency of the manufacturing industry in the CPUA generally shows a pattern of "higher efficiency in the middle, lower efficiency at the edges", and there is a situation of regional development imbalance in the high-quality development level of the manufacturing industry in the 30 regions.

Keywords: Central Plains Urban Agglomeration (CPUA); High-quality development; Three-stage DEA; Malmquist index

1 Introduction

The high-quality development of the manufacturing industry is one of the key points of China's economic tasks in 2021. In this regard, the manufacturing industry of the CPUA holds a significant position nationally, becoming the main pillar industry in this region. Especially in provinces such as Shandong, Henan, Hebei, and Anhui, being among China's top ten manufacturing provinces, they contribute significantly to the economy of the CPUA. Effectively utilizing the strategic opportunities of high-quality economic development could greatly promote the further development of both the economy and manufacturing industry in the CPUA. However, the manufacturing industry in the CPUA is currently in a state of "being large but not strong". Moreover, there is a significant disparity in the level of manufacturing development among cities in the agglomeration. For instance, in 2018, the net profit of the manufacturing industry in 30 prefecture-level cities of the CPUA totaled 6053.14 billion yuan, with Zhengzhou, Luoyang, Jiaozuo, Xuchang, and Zhoukou cities earning profits of 623.23 billion yuan, 388.65 billion yuan, 377.83 billion yuan, 396.71 billion yuan, and 434.28 billion yuan, respectively, accounting for 10.30%, 6.42%, 6.24%, 6.55%, and 7.17% of the agglomeration's total. In contrast, the operating profits of Bengbu and Jiyuan cities only accounted for 1.59% and 1.12%, respectively. If the current situation of uneven development of manufacturing in various regions continues, it will severely hinder the high-quality development of both the manufacturing industry and the economy in the CPUA.

The manufacturing industry plays a pivotal role in the economy, and in recent years, a substantial amount of literature has emerged on how to develop the manufacturing industry efficiently in various provinces. Reviewing the literature reveals that the main method for studying the efficiency of manufacturing development is the DEA model. He et al. [1] calculated the innovation efficiency of China's green low-carbon listed companies from 2016 to 2020 and found that under homogeneous conditions, the innovation efficiency of green low-carbon companies is at a lower level, mainly restricted by scale efficiency, with PTE showing scale heterogeneity. Yan et al. [2] found that R&D investment in Jiangsu's listed manufacturing companies has been increasing year by year, but the overall innovation performance has not reached an optimal state, mainly due to low PTE, necessitating an improvement in resource allocation efficiency. Xu and Lu [3] used the Banker, Charnes, and Cooper (BCC) Model of the DEA to measure the input-output efficiency of 60 listed manufacturing companies in Shanghai, Jiangsu, Zhejiang, and Anhui provinces, concluding that the comprehensive efficiency in the Yangtze River Delta region is low and there are significant differences in comprehensive efficiency among regions. Cui and Li [4] used the DEA-BBC and AHP models to conduct an empirical analysis of 21 specific industries in Qinghai's manufacturing industry, concluding that Qinghai's manufacturing industry overall lacks comparative advantages and exhibits significant internal developmental disparities. Zhang et al. [5] used the DEA-BCC and Malmquist index models to calculate the green innovation technology efficiency of 22 sub-industries in Shanxi's manufacturing industry, finding that the green technology innovation efficiency of various sub-industries in Shaanxi's manufacturing industry is low, but the overall trend is upward. Many scholars mainly use the first-stage DEA model in analyzing manufacturing efficiency, but the first-stage DEA model does not consider the impact of environmental variables on the efficiency evaluation of decision-making units [6], which may lead to the efficiency values being underestimated or overestimated, and the model's assumptions are inappropriate [7]. Although some scholars have considered the impact of environmental factors, they have only conducted static analyses of manufacturing efficiency using the three-stage DEA model, making it difficult to discern its dynamic trends [2]. Entering the 21st century, the DEA model remains the main model for efficiency research [8]. Moreover, a literature review reveals that there are currently no studies combining the DEA and Malmquist index models to examine the high-quality development of manufacturing in the five provinces of the CPUA (Henan, Hebei, Shandong, Shanxi, and Anhui). Therefore, based on the manufacturing efficiency of 30 prefecture-level cities in these five provinces of the CPUA, it is of significant research and practical importance to use a combined approach of the three-stage DEA and Malmquist index models to analyze both the static and dynamic trends of manufacturing efficiency in the CPUA, and to study how to achieve high-quality development in its manufacturing industry.

2 Research Methods

2.1 Three-Stage DEA Model

The three-stage DEA model is an improvement on the traditional DEA model. The efficiency of high-quality development is influenced not only by intrinsic conditions but also by management levels, external environmental factors, and random errors. The traditional DEA model does not account for these factors when calculating efficiency values, leading to inevitable biases in the derived efficiency values. Huang et al. [9] introduced the three-stage DEA method, which is capable of eliminating the effects of environmental factors, random error interference, and management inefficiencies, thereby yielding more accurate efficiency values. It is a new and effective evaluation method designed for multi-index input and output problems [10]. Developed by the renowned operational researchers Charnes and Cooper in 1978, DEA is based on the principle of "relative efficiency" and uses mathematical programming principles, it is an innovative and effective method for addressing multi-index input and output issues . DEA enables the quantitative assessment of analyzable entities of decision-making units (hereinafter referred to as DMUs) [11]. The evaluation is based on three types of efficiency: Total Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE). The relationship among these three efficiencies is as follows:

$$\mathrm{TE} = \mathrm{SE} \times \mathrm{PTE}$$

2.1.1 First stage

There are two models in the first stage of DEA: BCC model and Charnes, Cooper, and Rhodes (CCR) model. The CCR model is used to analyze input and output efficiency when scale returns are constant. However, in the actual operation of manufacturing, the condition of constant scale returns does not exist. Therefore, the CCR model should be discarded, and the BCC model, which allows for variable scale returns, should be used for calculation using Deap 2.1. The formula for the BCC model is as follows:

$$
s.t.\begin{cases} \min\theta \\ \sum_{j=1}^{n} x_j\lambda_j + s^- = \theta x_0 \\ \sum_{j=1}^{n} y_j\lambda_j + S^+ = y_0 \\ \lambda_j \geq 0, \quad j=1,\ldots n, \theta \text{ No constrain} \\ S^- \geq 0, S^+ \geq 0 \end{cases}
$$

where, θ represents the efficiency score of a DMU, j is the number of DMUs, epresent input excess and output shortfall, respectively; x_j is the input, y_j is the output, and λ_i is the proportion of the j-th suitable combination. If both S^- and S^+ are 0 and θ = 1, then it indicates an optimal allocation state. If θ = 1 but either S^- or $S^+ \neq 0$, it indicates weak efficient DEA; the smaller the values of S^- and S^+ and the closer θ is to 1, the more efficient the DMU is. If $\theta < 1$, it indicates that DEA efficiency is ineffective [12].

2.1.2 Second stage

Since the BCC model does not consider the impact of environmental indicators, this can lead to biases in efficiency results. Therefore, it is necessary to use the SFA model to eliminate the disturbances caused by environmental factors and random errors. Generally, if the first stage DEA model is input-oriented, then the input slack is chosen as the dependent variable; if the DEA model is output-oriented, then the output slack is selected. In this paper, the first stage DEA model is input-oriented, so the input slack is the explained variable. Conducting a regression on all input slacks offers higher degrees of freedom and statistical efficiency, while regressing each type of input slack separately determines the impact of environmental variables on each type of input slack, as the impact of environmental variables on each input element might differ. The specific method is as follows: The production function $F(x)$ indicates the maximum output given the input x. However, in reality, it is often difficult for producers to reach the maximum output frontier, so it is assumed that the output of producer i is:

$$
Y_i = \mathrm{f}\left(X_i, \beta\right) \zeta_i
$$

where, β is the parameter to be estimated, ξ_i represents the efficiency level of producer i, satisfying $0 < \xi_i$. Since the production function is also affected by random shocks, the formula can be adjusted as:

$$
Y_i = \mathrm{f}\left(X_i, \beta\right) \zeta_i e^{v_i}
$$

where, $e^{v_i} > 0$ is the random shock, meaning that the production function's frontier $\mathrm{f}\left(X_i, \beta\right) e^{v_i}$ is under randomness [13].

After adjusting the original output indicator data through SFA, the efficiency of each DMU is recalculated using Deap 2.1. The efficiency values obtained at this stage have already eliminated the impacts caused by environmental factors and random disturbances.

2.1.3 Third stage DEA method

Through the second stage SFA regression process, the input quantities that have been adjusted to remove environmental disturbances and random perturbations are obtained, by inputting these adjusted inputs and the original outputs into the traditional DEA model, the efficiency values are recalculated. The results obtained are the efficiency values that have been adjusted to remove the impacts of environmental and random disturbances.

2.2 Malmquist Index Method

The Malmquist Productivity Index (MPI) is based on the benchmark technology that satisfies Constant Returns to Scale (CRS) [14]. It was originally proposed by Sten Malmquist, who introduced a quantity index to analyze input consumption. Kwon et al. [15] suggested establishing an MPI based on DEA, using two measures proposed by Farrell [16] and Cave [17]: efficiency and productivity, to assess efficiency and technological changes . However, this method has certain limitations: it can only compare production efficiency at two points in time and is unable to analyze long-term production efficiency trends. Furthermore, the Malmquist index method relies on the DEA model in its calculation process, requiring high accuracy and completeness of data. The specific derivation formula is as follows:

Assuming: there are n DMUs to be studied, each DMU has p types of input indicators and q types of output indicators in period t; $X_n^t = \left(X_{1n}^t, X_{2n}^t, \cdots, X_{pn}^t\right)$ represents the input data of the n-th DMU in period t, and $Y_n^t = \left(Y_{1n}^t, Y_{2n}^t, \cdots, Y_{qn}^t\right)$ represents the output indicators of the n-th DMU in period t (all data are positive, t=1,2,...,T).

Under variable scale returns, the distance function of X^t, Y^t in period t is $D_V^t\left(X^t, Y^t\right)$, and in period t+1 is $D_V^{t+1}\left(X^t, Y^t\right)$, then the distance function in period t is $D_V^t\left(X^{t+1}, Y^{t+1}\right)$, and in period t+1 is $D_V^{t+1}\left(X^{t+1}, Y^{t+1}\right)$.

For period t, the change in technical efficiency from t to t+1 is:

$$M^t = \frac{D_c^t\left(X^{t+1}, Y^{t+1}\right)}{D_c^t\left(X^t, Y^t\right)}$$

For period t+1, the formula for the change in technical efficiency from t to t+1 is:

$$M^{t+1} = \frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}\right)}{D_c^{t+1}\left(X^t, Y^t\right)}$$

In summary, the average formula of the Malmquist index model's productivity index is:

$$\mathrm{M}\left(X^t, Y^t, X^{t+1}, Y^{t+1}\right) = \left(M_t \cdot M_{t+1}\right)^{\frac{1}{2}} = \left[\left(\frac{D_c^t\left(X^{t+1}, Y^{t+1}\right)}{D_c^t\left(X^t, Y^t\right)}\right)\left(\frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}\right)}{D_c^{t+1}\left(X^t, Y^t\right)}\right)\right]^{\frac{1}{2}}$$

where, t represents the period, D_c^t and D_c^{t+1} represent the distance functions between periods t and t+1, with $\left(X^t, Y^t\right)$ and $\left(X^{t+1}, Y^{t+1}\right)$ representing the input-output data for periods t and t+1, respectively. If the efficiency result is less than 1, it indicates a decline in total factor productivity from period t to t+1, and vice versa [15].

3 Indicator Establishment and Data Source

3.1 Indicator Establishment

Before conducting a DEA analysis, it is essential to define the DMUs and the indicator system. Since there is no standardized DEA input-output indicator system for the manufacturing industry, the selection of indicators must be based on rationality. By reviewing core literature and materials related to the manufacturing industry, it is noted that many scholars use the number of business units main business cost of the manufacturing industry [1, 3], and total assets [1, 3] as input variables, and total profit [1, 3, 16], main business revenue [16] as output variables. This paper also adopts these indicators as the input and output indicators for the manufacturing industry. Furthermore, it is widely accepted in the academic community that the measurement of economic development level should consider quality issues, not just GDP, and a multi-indicator comprehensive evaluation system should be constructed to measure the level of high-quality economic development [18]. Considering principles of scientificness, comprehensiveness, and high-quality factors, this paper adds nine necessary and uncontrollable variables as environmental indicators: urban permanent population, industrial sulfur dioxide emissions, urban employee basic pension insurance coverage, GDP of each city, R&D internal expenditure, goods export volume, goods import volume, road freight volume, and household deposit balance [19].

3.2 Data Source

The DMUs selected for this study are 30 prefecture-level cities from the five provinces of the CPUA, namely Henan Province (Zhengzhou, Kaifeng, Luoyang, Nanyang, Anyang, Shangqiu, Xinxiang, Pingdingshan, Xuchang, Jiaozuo, Zhoukou, Xinyang, Zhumadian, Hebi, Puyang, Luohe, Sanmenxia, Jiyuan), Shanxi Province (Changzhi, Jincheng, Yuncheng), Shandong Province (Liaocheng, Heze), Anhui Province (Suzhou, Huaibei, Fuyang, Bozhou, Bengbu), and Hebei Province (Xingtai, Handan). The manufacturing industry data from 2013-2018 primarily come from the statistical yearbooks of Henan, Shanxi, Shandong, Anhui, and Hebei provinces for the years 2014-2019, namely the Henan Statistical Yearbook, Shanxi Statistical Yearbook, Shandong Statistical Yearbook, Anhui Statistical Yearbook, Hebei Statistical Yearbook, and China City Statistical Yearbook. Some data are also sourced from the Statistical Communiques on National Economic and Social Development of the respective cities for the years 2014-2019.

Building upon the data source description, Table 1 is set to be revealed next. This table methodically outlines the chosen indicators for our study, encompassing a comprehensive range of variables including inputs, outputs, and environmental factors. These indicators are pivotal in evaluating the manufacturing industry's performance, providing a deeper insight into this study's analytical framework.

Table 1. Selection of indicators

Research Subject	Indicator Type	Indicator
30 Cities of 5 Provinces in the CPUA	Input Indicators	Number of Business Units (units) Main Business Cost (100 million yuan) Total Assets (100 million yuan)
	Output Indicators	Total Profit (100 million yuan) Main Operating Revenue of Manufacturing Industry (100 million yuan)
	Environmental Variables	Urban Permanent Population of Each City (10 thousands people) Industrial Sulfur Dioxide Emissions (tons) GDP of Each City (100 million yuan) R&D Internal Expenditure (ten thousand yuan) Goods Export Volume (ten thousand yuan) Goods Import Volume (ten thousand yuan) Road Freight Volume (ten thousand tons) Household Deposit Balance (ten thousand yuan) Urban Employee Basic Pension Insurance Coverage (number of people)

4 Empirical Analysis

4.1 Results of the First Stage DEA

An analysis of the manufacturing input-output indicator data from 2017 to 2022 using Deap 2.1 reveals the comprehensive efficiency results of the manufacturing industry in each city of the CPUA, as shown in Table 2, it is apparent that without excluding the interference of environmental factors, specifically, the cities of Luohe and Jiyuan have consistently effective comprehensive efficiency from 2017 to 2022. Zhoukou City has maintained effective comprehensive efficiency for four consecutive years from 2019 to 2022. Jincheng City has been effective in five out of the six years. Although Zhengzhou City's comprehensive efficiency is not effective every year, its annual efficiency value exceeds the average efficiency of all cities, indicating that the manufacturing development level in these cities is relatively good. However, overall, the comprehensive efficiency of the manufacturing industry in the cities of the CPUA is rather average, presenting a state of being "large but not strong".

4.2 Results of the Second Stage DEA

In the second stage of DEA, the slack variables of various input indicators for the manufacturing industry in the 30 prefecture-level cities of the CPUA, obtained from the first stage DEA, are used as the dependent variables. Nine environmental variables are employed as explanatory variables: the urban permanent population of each city, industrial sulfur dioxide emissions, GDP of each city, R&D internal expenditure, goods export volume, goods import volume, road freight volume, household deposit balance, and the number of urban employees covered by basic pension insurance. Using Frontier 4.1, SFA regression analysis was conducted for each year's data. Since the trends in the data are roughly similar each year, for the sake of brevity, this paper presents and validates the SFA analysis results for the year 2022. The regression analysis results for 2022 are shown in Table 3.

When the regression coefficient is positive, increasing the input of environmental variables will reduce the output of the manufacturing industry or cause wastage of manufacturing input variables. Conversely, when the regression coefficient is negative, increasing the input of environmental variables will increase the manufacturing output or save manufacturing inputs, thereby reducing the slack in manufacturing inputs [20]. From Table 3, it is evident that the urban permanent population, GDP of each city, goods import volume, and the number of urban employees covered by basic pension insurance have a positive correlation with various input slack variables. This implies that GDP growth is detrimental to the comprehensive efficiency of the manufacturing industry. This could be due to increased inputs as these indicators rise, but the output does not increase proportionally, leading to redundancy. On the other hand, industrial sulfur dioxide emissions, R&D internal expenditure, goods export volume, and household deposit balance are beneficial for the comprehensive efficiency of the manufacturing industry. Increasing these input variables will increase manufacturing output or save inputs, reducing the slack in manufacturing inputs. The positive correlation between sulfur dioxide emissions and manufacturing efficiency indicates that the scale of manufacturing input has not yet reached its peak and can be appropriately increased.

According to Table 3, the σ^2 value for the manufacturing industry in 2022 is relatively large, and the γ values are close to 1 and significant at the 1% level. This indicates that inefficiencies in management and random errors play a significant role in the composite error term, with management inefficiencies being predominant. This suggests that these values occupy a substantial proportion of the total variance, indicating that redundancies caused by environmental factors such as the GDP of each city play a dominant role. Therefore, it is necessary to adjust the original input quantities [21]. Additionally, the unilateral likelihood values of the three SFA models are significant at the 1% level, indicating that management factors in the inputs of the number of business units, main business costs, and total assets are significant. This further indicates that different environmental variables will cause varying degrees of input discrepancies, demonstrating the appropriateness and necessity of using SFA for further analysis of input variables. It also shows that the selected environmental variables indeed have a significant impact on the calculation results of the comprehensive efficiency of the manufacturing industry in the CPUA.

Table 2. Results of comprehensive efficiency measurement of manufacturing in cities

Year Region	2017	2018	2019	2020	2021	2022
Zhengzhou	0.988	0.996	1	0.988	0.954	0.937
Kaifeng	0.932	0.936	0.948	0.957	0.987	0.947
Luoyang	0.945	0.945	0.938	0.945	0.936	0.946
Ringdingshan	0.967	0.951	0.946	0.951	0.921	0.881
Anyang	0.943	0.959	0.934	0.951	0.915	0.917
Hebi	0.932	0.943	0.954	0.959	0.967	0.986
Xinxiang	0.912	0.923	0.929	0.938	0.917	0.915
Jiaozuo	0.952	0.971	0.967	0.963	0.955	0.999
Puxang	0.97	0.978	0.967	0.966	1	0.897
Xuchang	0.975	0.988	0.980	0.990	0.974	0.987
Luohe	1	1	1	1	1	1
Sanmenxia	1	1	0.994	0.972	0.939	1
Nanyang	0.965	0.945	0.945	0.947	0.929	0.932
Shangaiu	0.918	0.922	0.918	0.937	0.932	1
Xinyang	0.934	0.94	0.968	0.981	0.962	0.97
Zhoukou	0.99	0.993	1	1	1	1
Zhumadian	0.915	0.93	0.942	0.954	0.945	1
Jixuan	1	1	1	1	1	1
Changzhi	1	0.984	0.979	1	1	1
Jincheng	1	1	1	0.965	1	1
Yuncheng	0.913	0.921	0.916	0.925	0.922	0.96
Liaocheng	0.967	1	1	0.992	0.866	0.866
Heze	1	1	1	0.98	1	0.966
Huaibei	0.927	0.928	0.917	0.933	0.948	0.970
Bozhou	1	0.979	0.998	1	0.985	0.999
Suzhou	0.904	0.922	1	0.941	0.964	1
Bengbu	0.965	0.932	0.949	1	0.942	0.945
Fuxang	0.946	0.947	0.945	0.961	0.952	1
Xingarai	1	0.906	0.919	0.936	0.921	0.738
Handan	0.927	0.934	0.916	0.931	0.904	0.944
Mean	0.956	0.960	0.959	0.963	0.952	0.954

4.3 Third Stage DEA

After adjusting the original input data using the SFA model, a reanalysis of the manufacturing input-output indicators with Deap 2.1 was conducted. The results of the comprehensive efficiency of manufacturing in various areas of the CPUA are presented in Table 4. Overall, after adjustment, the average comprehensive efficiency of each area has decreased compared to before the adjustment. Specifically, Zhengzhou City, which was only efficient in 2019 before the adjustment, showed effective comprehensive efficiency for six consecutive years after the adjustment. Before the adjustment, the comprehensive efficiency of Luohe, Zhoukou, and Jiyuan cities was effective; however, after the adjustment, Zhoukou City showed inefficiency from 2017 to 2019, Luohe City was only efficient in 2017 with the remaining five years becoming inefficient, and Jiyuan City turned completely inefficient with efficiency values below the average for six consecutive years. The comprehensive efficiency of Luoyang, Xinxiang, Jiaozuo, Xuchang, and Nanyang cities, although not consistently at 1, exceeded the average each year. After eliminating the impact of environmental factors and random disturbances, the efficiency of Hebi, Xinyang, and Bozhou cities was below the average, indicating that the manufacturing industry in these cities is greatly affected by environmental fluctuations. Ranking the average comprehensive efficiency of the 30 cities from 2017 to 2022 from highest to lowest, the order is Zhengzhou City (1) > Heze City (0.997) > Zhoukou City (0.981) > Xuchang City (0.980) > Luoyang City (0.974) > Liaocheng City (0.966) > Jiaozuo City, Handan City (0.965) > Xinxiang City (0.940) > Nanyang City (0.936) > Luohe City (0.927) > Anyang City (0.916) > Shangqiu City (0.905) > Kaifeng City (0.894) > Average Value (0.889) > Pingdingshan City (0.888) > Zhumadian City (0.882) > Puyang City (0.877) > Bengbu City (0.8757) > Sanmenxia City (0.8756) > Xingtai City (0.874) > Huaibei City (0.859) > Fuyang City (0.855) > Changzhi City (0.851) > Xinyang City (0.848) > Hebi City (0.809) > Yuncheng City (0.808) > Suzhou City (0.787) > Jincheng City (0.783) > Bozhou City (0.721) > Jiyuan City (0.717).

Table 3. Results of phase II SFN measurements for 2018

Dependent Variable Independent Vartable	**Number of Business Units - Slack Variable**	**Main Business Cost - Slack Variable**	**Total Assets - Slack Variable**
Urban Permanent Population of Each City	$3.34E-01$	$1.86E-01$	$1.75E-01$
	$(1.42E+00)$	$(9.41E-01)$	$(2.29E-01)$
Industrial Sulfur Dioxide Emissions	$-8.07E-03^{***}$	$-4.41E-03^{*}$	$-6.01E-03^{*}$
	$(-2.87E+00)$	$(-1.72E+00)$	$(-1.87E+00)$
GDP of Each City	$2.85E-01^{***}$	$4.09E-02$	$9.12E-02$
	$(5.71E+00)$	$(9.12E-01)$	$(8.44E-01)$
R&D Internal Expenditure	$-4.45E-04^{***}$	$-8.33E-05$	$-2.02E-04$
	$(-2.97E+00)$	$(-7.66E-01)$	$(-8.04E-01)$
Goods Export Volume	$-2.69E-04^{***}$	$-5.85E-05^{***}$	$-2.79E-05$
	$(-7.13E+00)$	$(-7.99E+00)$	$(-8.00E-01)$
Goods Import Volume	$3.61E-04^{***}$	$5.66E-05^{***}$	$1.89E-07$
	$(4.19E+00)$	$(1.10E+01)$	$(4.87E-03)$
Road Freight Volume	$1.42E-02^{***}$	$4.72E-03^{**}$	$4.92E-03^{**}$
	$(3.78E+00)$	$(2.17E+00)$	$(2.13E+00)$
Household Deposit Balance	$-1.56E-05^{***}$	$-7.42E-06^{**}$	$-1.23E-05^{*}$
	$(-2.76E+00)$	$(-2.40E+00)$	$(-1.84E+00)$
Number of Urban Employees Covered by Basic Pension Insurance	$1.43E-04^{*}$	$2.10E-04^{*}$	$2.44E-04$
	$(1.72E+00)$	$(1.75E+00)$	$(1.53E+00)$
σ^2	$8.35E+04^{***}$	$2.82E+04^{***}$	$5.20E+04^{***}$
γ	0.99^{**}	0.99^{**}	0.99^{***}
Log Value	-194.05	-170.72	-182.46
LR Unilateral Test	12.35^{***}	26.01^{***}	20.87^{***}

Note: *, **, and *** respectively indicate significance at the 10%, 5%, and 1% statistical levels; values in parentheses are t-values.

To more visually analyze the disparity in manufacturing development efficiency among cities in the CPUA, software Arcgis was used to classify the comprehensive manufacturing efficiency of the 30 cities over six consecutive years into five levels, as shown in Figure 1. Specifically, the central cities in the CPUA exhibited higher manufacturing efficiency. The manufacturing efficiency of Jiyuan City was consistently lower within the group. Over time, significant improvements in manufacturing efficiency were observed in eastern cities like Changzhi, Jincheng, and Yuncheng, as well as western cities like Suzhou, Bengbu, and Fuyang. Conversely, northern cities such as Xingtai, Liaocheng, Puyang, and southern city Xinyang experienced significant declines in manufacturing efficiency. Overall, the CPUA's manufacturing industry exhibited a pattern of high quality and efficiency, with a spatial distribution of "higher efficiency in the center, lower on the edges", and regional development disparities among the 30 cities.

4.4 Analysis of the Decomposition of Comprehensive Efficiency

The relationship between TE, PTE, and SE suggests that the efficiency of STE and SE directly determines the effectiveness of TE. The decomposition results of comprehensive efficiency from 2017 to 2022 for the CPUA are shown in Table 5 and Figure 2. After excluding environmental and random factors, Table 6 provides the distribution of manufacturing efficiency for each year to compare how often they reach the production frontier.

Overall, based on the decomposition results, the highest comprehensive efficiency was 0.925 in 2022, with the lowest at 0.813 in 2019, indicating an average input waste of 11.1% over six years. This suggests that the input resources in the CPUA were not fully utilized. Further decomposition of total technical efficiency revealed a slow declining trend in PTE, as shown in Figure 2, reaching a maximum of 0.925 in 2018 and a minimum of 0.984 in 2019, with an average of 0.986, indicating 1.4% input waste. SE was at its lowest at 0.826 in 2019 and highest at 0.976 in 2018, averaging 0.901, indicating 9.9% input waste. From 2017 to 2022, the proportion of areas not reaching optimal comprehensive efficiency ranged from 70% to 90%, those not reaching optimal PTE ranged from 23% to 53%, and those not reaching optimal SE ranged from 77% to 90%. This indicates that from 2017 to 2022, the PTE of the manufacturing industry in the CPUA was stable and relatively good, with the overall low comprehensive efficiency mainly due to poor SE [22].

Table 4. Comparison of the results of the comprehensive efficiency measurements of each city before and after the adjustment

Year/Region	2017		2018		2019		2020		2021		2022	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Zhengzhou	0.945	1	0.996	1	1	1	0.99	1	0.954	1	0.937	1
Kaifeng	0.932	0.916	0.936	0.878	0.948	0.838	0.957	0.929	0.93	0.892	0.947	0.908
Luoyang	0.923	1	0.945	0.972	0.938	0.928	0.945	0.972	0.936	0.976	0.946	0.995
Pingdingshan	0.954	0.911	0.951	0.88	0.946	0.808	0.951	0.92	0.921	0.928	0.881	0.880
Anyang	0.942	0.928	0.959	0.928	0.934	0.878	0.951	0.951	0.915	0.891	0.917	0.921
Hebi	0.932	0.976	0.942	0.788	0.954	0.731	0.959	0.826	0.95	0.843	0.986	0.847
Xinxiang	0.912	0.879	0.93	0.945	0.929	0.905	0.938	0.964	0.917	0.926	0.915	0.957
Jiaozuo	0.952	0.926	0.971	0.952	0.970	0.914	0.963	1	0.955	1	0.999	0.996
Puyang	0.970	0.915	0.978	0.902	0.970	0.85	0.966	0.896	1	0.924	0.897	0.775
Xuchang	0.975	0.972	0.988	0.957	0.980	0.953	0.990	0.998	0.974	1	0.987	1
Luohe	1	1	1	0.912	1	0.865	1	0.954	1	0.933	1	0.897
Sanmenxia	1	0.916	1	0.905	0.994	0.816	0.972	0.854	0.939	0.84	1	0.923
Nanyang	0.94	0.954	0.945	0.949	0.945	0.895	0.947	0.946	0.929	0.936	0.932	0.935
Shangqiu	0.918	0.907	0.922	0.889	0.918	0.809	0.937	0.909	0.932	0.915	1	1
Xinyang	0.934	0.874	0.897	0.857	0.978	0.754	0.981	0.847	0.962	0.881	0.907	0.873
Zhoukou	0.99	1	0.993	0.927	1	0.959	1	1	1	1	1	1
Zhumadian	0.915	0.895	0.93	0.88	0.942	0.789	0.954	0.894	0.945	0.898	1	0.935
Jiyuan	1	0.746	1	0.721	1	0.600	1	0.706	1	0.768	1	0.76
Changzhi	1	0.865	0.984	0.79	0.979	0.619	1	0.835	1	0.996	1	1
Jincheng	1	0.806	1	0.722	1	0.573	0.965	0.734	1	0.888	1	0.976
Yuncheng	0.913	0.844	0.921	0.79	0.916	0.625	0.925	0.725	0.922	0.928	0.96	0.937
Liaocheng	0.967	1	1	1	1	1	0.992	1	0.866	0.917	0.866	0.877
Heze	1	1	1	1	1	1	0.98	1	1	1	0.92	0.981
Huaibei	0.927	0.895	0.928	0.852	0.917	0.789	0.933	0.823	0.948	0.917	0.97	0.88
Bozhou	1	0.76	0.979	0.626	0.998	0.557	1	0.737	0.985	0.81	0.999	0.834
Suzhou	0.904	0.73	0.922	0.715	1	0.674	0.941	0.821	0.964	0.824	1	0.959
Bengbu	0.955	0.834	0.932	0.812	0.949	0.782	1	1	0.942	0.869	0.945	0.958
Fuyang	0.946	0.815	0.947	0.795	0.945	0.738	0.961	0.875	0.952	0.909	1	1
Xingtai	1	0.949	0.906	0.892	0.919	0.818	0.936	0.924	0.921	0.915	0.738	0.748
Handan	0.927	1	0.934	0.952	0.916	0.915	0.931	0.94	0.904	0.981	0.944	1
Mean	0.957	0.904	0.959	0.873	0.963	0.813	0.966	0.899	0.952	0.917	0.955	0.925

After decomposing the comprehensive efficiency, from the perspective of PTE, Zhengzhou, Zhoukou, Changzhi, Jincheng, Heze, Bozhou, and Fuyang cities had effective PTE for six consecutive years. Jiaozuo, Luohe, Jiyuan, Suzhou, Xuchang, Yuncheng, Liaocheng, Bengbu, and Handan cities had at least four years of effective PTE in six years, indicating relatively good performance. From the perspective of SE, only Zhengzhou City consistently had effective SE in 2021-2022. Zhoukou, Liaocheng, and Heze cities had at least four years of effective SE in six years. It was also found that cities with low PTE in the CPUA from 2017 to 2022 also had low SE.

4.5 Decomposition Results and Empirical Analysis of the Malmquist Index Model

Using the adjusted input indicators and the original output indicators, the TFP for the 30 cities in the CPUA was calculated using the Malmquist Index model, with results shown in Table 7. Overall, the TFP of the CPUA from 2017 to 2022 showed a downward trend, with an average annual decline of 0.8% after excluding environmental factors, though it increased compared to before the adjustment. Specifically, Jincheng City had the highest manufacturing TFP at 1.055, while Puyang City had the lowest at 0.938.

Comparing the TFP of each region's manufacturing industry before and after SFA adjustment, as shown in Table 8, it is found that TFP in most areas declined, indicating that TFP was overestimated in many areas due to environmental factors and random errors. The manufacturing TFP in Zhengzhou, Luoyang, Anyang, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Nanyang, Zhoukou, Zhumadian, Liaocheng, and Handan regions improved, suggesting that TFP was underestimated in these areas due to environmental and random factors. Among all regions in the CPUA, Bengbu City showed the largest change in TFP before and after adjustment, indicating the greatest impact of environmental and random factors [23].

Table 5. The results of the comprehensive efficiency breakdown of cities after adjustment

Year/Region	**PTE**						**SE**					
	2017	**2018**	**2019**	**2020**	**2021**	**2022**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Zhengzhou	1	1	1	1	1	1	1	1	1	1	1	1
Kaifeng	0.999	0.999	0.993	0.989	0.936	0.96	0.916	0.879	0.843	0.939	0.953	0.945
Luoyang	1	1	0.963	0.985	0.981	0.998	1	0.972	0.964	0.987	0.995	0.997
Pingdingshan	0.996	1	1	1	0.958	0.902	0.914	0.88	0.808	0.920	0.968	0.975
Anyang	1	1	0.994	0.999	0.945	0.987	0.928	0.928	0.883	0.951	0.944	0.933
Hebi	0.978	0.991	0.975	0.969	0.994	1	0.834	0.795	0.75	.853	.848	0.847
Xinxiang	0.984	1	0.997	1	0.949	0.987	0.958	0.945	0.908	0.964	0.976	0.97
Jiaozuo	0.978	1	1	1	1	1	0.947	0.952	0.914	1	1	0.996
Puyang	0.994	0.999	0.971	0.954	1	0.965	0.919	0.903	0.875	0.939	0.924	0.803
Xuchang	0.999	0.996	1	1	1	1	0.973	0.961	0.953	0.998	1	1
Luohe	1	1	1	1	1	0.98	1	0.912	0.865	0.954	0.933	0.916
Sanmenxia	1	1	0.934	0.943	0.965	1	0.916	0.905	0.874	.906	871	0.923
Nanyang	1	1	0.978	0.978	0.949	0.957	0.954	0.949	0.915	0.967	0.986	0.977
Shangqiu	1	1	0.946	0.965	0.961	1	0.907	0.889	0.855	0.942	0.952	1
Xinyang	0.999	1	0.938	0.928	0.961	0.941	0.875	0.857	0.804	0.912	0.916	0.928
Zhou	1	1		1	1	1	1	0.927	0.959	1	1	1
Zhum	0.999	0.999	0.94	0.96	0.94	0.986	0.896	0.881	0.839	0.931	0.953	0.949
yuan	1	1	0.961	1	1	1	0.746	0.721	0.624	0.706	0.768	0.76
Changzhi	1	1	1	1	1	1	0.865	0.79	0.619	0.835	0.996	1
Jincheng	1			1	1		0.806	0.722	0.573	0.734	0.888	0.976
eng	0.979	0.995	1	1	1	1	0.862	0.794	0.625	0.725	0.928	0.937
Liaocheng	1	1	1	1	0.919	0.88	1	1	1	1	0.998	0.993
Heze	1	1	1	1	1	1	1	1	1	1	1	0.981
Huaibei	0.982	0.992	0.982	0.914	0.983	0.956	0.911	0.859	0.803	0.900	0.933	0.92
Bozhou	1	1	1	1	,	1	0.76	0.626	0.557	0.737	0.81	0.834
Suzhou	1	1	1	0.98	1	1	0.7	0.715	0.674	0.838	0.824	0.959
Bengbu	1	1	0.984	1	0.956	1	0.834	0.812	0.794	1.000	0.909	0.958
Fuyang	1	1	,		,		0.815	0.795	0.738	0.875	0.909	1
Xingtai	1	1	0.989	0.999	0.961	0.79	0.949	0.892	0.827	0.925	0.952	0.946
Handan	1	1	0.984	1	0.988	1	1	0.952	0.931	0.940	0.993	1
Mean	0.996	0.999	0.984	0.985	0.978	0.976	0.907	0.874	0.826	0.913	0.938	0.947

Table 6. Distribution of efficiency in the manufacturing industry of the CPUA

Year **Efficiency**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
TE $= 1$	0.23	0.10	0.10	0.20	0.17	0.23
TE < 1	0.77	0.90	0.90	0.80	0.83	0.77
PTE $= 1$	0.63	0.77	0.47	0.57	0.47	0.57
PTE < 1	0.37	0.23	0.53	0.43	0.53	0.43
SE $= 1$	0.23	0.10	0.10	0.20	0.17	0.23
SE < 1	0.77	0.90	0.90	0.80	0.83	0.77

Note: TE represents Total Efficiency, PTE represents Pure Technical Efficiency, and SE represents Scale Efficiency

Looking at the time series, the TFP for the years 2017-2018, 2018-2019, 2020-2021, and 2021-2022 were 0.977, 0.843, 0.986, and 0.992, respectively, with average annual declines of 2.3%, 15.7%, 1.4%, and 0.8%. Combining these with the decomposition efficiency results from Table 7, the main reason for the decline in TFP in the CPUA's manufacturing industry is due to lagging technological progress. The TFP for 2019-2020 was 1.2, with an average growth rate of 20%, attributable to simultaneous increases in technical efficiency and technological progress during this period [24].

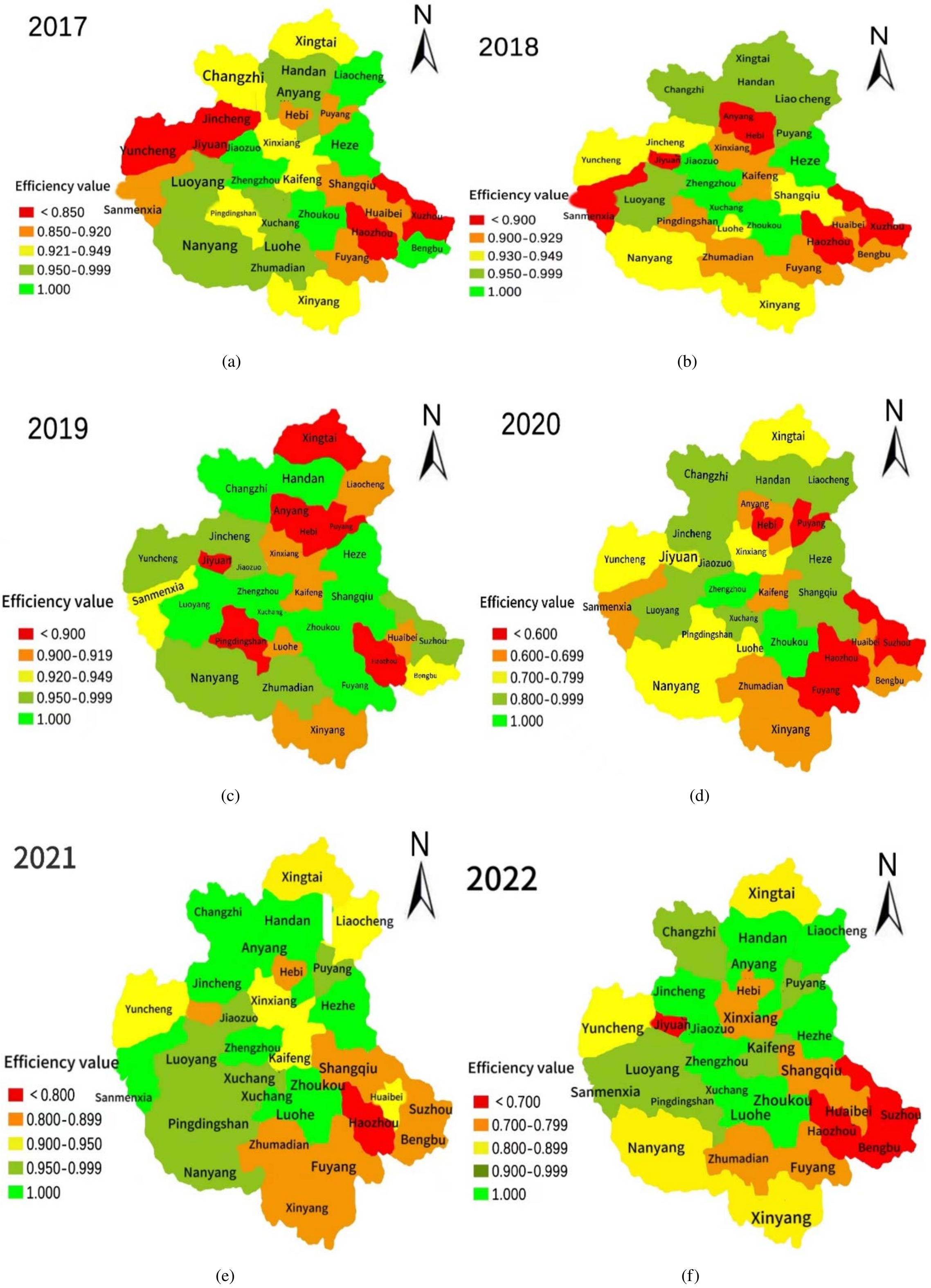

Figure 1. Spatial distribution of manufacturing integrated efficiency in the CPUA for 2017-2022

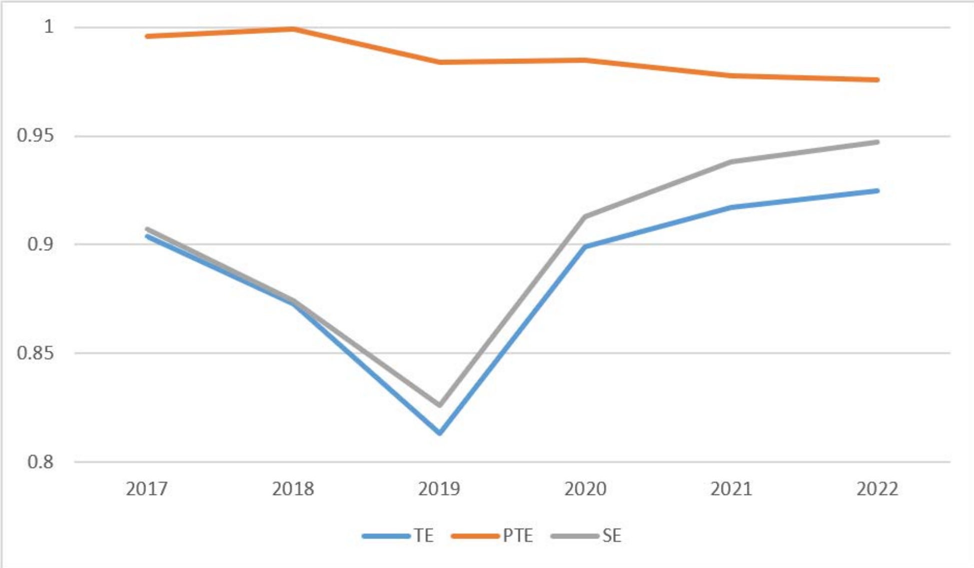

Figure 2. Trend chart of the average efficiency of the manufacturing industry in the CPUA

Table 7. TFP and its decomposition efficiency for manufacturing industries in cities in the CPUA before and after adjustment, 2017-2022

Year	Technological Efficiency (Effch)		Technological Progress (Techch)		Pure Technical Efficiency (Pech)		Scale Efficiency (Sech)		Total Factor Productivity (Tfpch)	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
2017 – 2018	1.003	0.964	0.988	1.013	0.998	1.003	1.004	0.961	0.991	0.977
2018 – 2019	1.003	0.925	0.99	0.912	0.998	0.985	1.005	0.939	0.993	0.843
2019 – 2020	1.003	1.115	1.036	1.076	1.007	1.001	0.996	1.114	1.04	1.2
2020 – 2021	0.986	1.023	0.995	0.965	0.993	0.993	0.993	1.03	0.981	0.986
2021 – 2022	1.002	1.008	0.936	0.979	1.001	0.997	1.001	1.011	0.938	0.987
Mean	0.999	1.005	0.989	0.988	0.999	0.996	1	1.009	0.988	0.992

Note: Tfpch = Effch×Techch; Effch = Pech×Sech

5 Summary and Development Suggestions

5.1 Summary

This paper, by applying the three-stage DEA model, eliminates the impact of environmental variables and random errors. Based on the indicator system data from 2017 to 2022 for 30 cities in the five provinces of the CPUA, an analysis was conducted on the input-output efficiency of the manufacturing industry in these cities. Furthermore, a dynamic analysis of the efficiency and TFP of the manufacturing industry over six years was carried out using the Malmquist index model. The research conclusions are as follows:

(1) The PTE of the 30 cities in the CPUA was stable and relatively good from 2017 to 2022, with the overall low comprehensive efficiency mainly due to poor SE. After decomposing the TE, from a PTE perspective, 16 cities including Zhengzhou, Zhoukou, Changzhi, Jincheng, Heze, Bozhou, Fuyang, Jiaozuo, Luohe, Jiyuan, Suzhou, Xuchang, Yuncheng, Liaocheng, Bengbu, and Handan showed relatively good manufacturing PTE. From a SE perspective, only Zhengzhou, Zhoukou, Liaocheng, and Heze showed relatively good SE; cities with lower PTE in the CPUA also had lower SE from 2017 to 2022.

(2) Before excluding the interference caused by environmental factors, the manufacturing high-quality development level of Luohe, Jiyuan, Zhoukou, Jincheng, Zhengzhou, and Changzhi was relatively good. However, overall, the TE of the manufacturing industry in the cities of the CPUA was average, presenting a state of being "large but not strong". After excluding environmental factors, the average TE of the 30 cities decreased compared to before the adjustment, indicating a significant impact of environmental factors on manufacturing efficiency.

(3) Based on the results of the SFA regression model, nine environmental variables significantly affected the efficiency of the manufacturing industry. The urban permanent population, GDP of each city, goods import volume, and the number of urban employees covered by basic pension insurance were detrimental to manufacturing efficiency.

This was because with the increase in GDP and other indicators, the input increased, but the output did not increase proportionally, leading to redundancy. Industrial sulfur dioxide emissions, R&D internal expenditure, goods export volume, and household deposit balance were beneficial for manufacturing efficiency.

(4) After excluding the impact of environmental factors, over the six years from 2017 to 2022, Zhengzhou City had the best high-quality development level in manufacturing, consistently effective. The areas with better manufacturing development included Heze, Zhoukou, Xuchang, Luoyang, Liaocheng, Jiaozuo, Handan, Xinxiang, Nanyang, Luohe, Anyang, Shangshui, and Kaifeng. The areas with weaker manufacturing development included Pingdingshan, Zhumadian, Puyang, Bengbu, Sanmenxia, Xingtai, Huaibei, Fuyang, Changzhi, Xinyang, Hebi, Yuncheng, Suzhou, Jincheng, Bozhou, and Jiyuan.

(5) After excluding the impact of environmental factors, the TFP of the manufacturing industry in some cities declined. Due to the influence of environmental factors and random errors, TFP was overestimated in many cities, such as Zhengzhou, Luoyang, Anyang, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Nanyang, Zhoukou, Zhumadian, Liaocheng, and Handan. Among all the cities in the CPUA, Bengbu City was the most affected by environmental factors and random errors. The main factor for the decline in TFP in the manufacturing industry of the CPUA was the inhibition of technological progress.

Table 8. Malmquist index and its breakdown before and after adjustment

	Before Adjustment					After Adjustment					
Region	**Effch**	**Techch**	**Pech**	**Sech**	**Tfpch**	**Region**	**Effch**	**Techch**	**Pech**	**Sech**	**Tfpch**
Zhengzhou	0.99	0.997	1	0.99	0.986	Zhengzhou	1	0.945	1	1	0.945
Kaifeng	1.004	0.996	1.002	1.001	1	Kaifeng	0.998	1.005	0.992	1.006	1.003
Luoyang	1.004	0.998	1.012	0.992	1.001	Luoyang	0.999	0.974	1	0.999	0.973
Pingdingshan	0.987	1.001	0.986	1	0.988	Pingdingshan	0.993	1.004	0.98	1.013	0.997
Anyang	0.995	0.995	0.996	0.999	0.989	Anyang	0.998	0.988	0.997	1.001	0.986
Hebi	1.011	0.984	1.003	1.009	0.996	Hebi	1.008	1.003	1.004	1.003	1.01
Xinxiang	1.001	0.989	0.999	1.001	0.99	Xinxiang	1.003	0.977	1.001	1.002	0.98
Jiaozuo	1.01	0.967	1	1.01	0.976	Jiaozuo	1.015	0.95	1.004	1.01	0.964
Puyang	0.984	0.958	1	0.985	0.943	Puyang	0.968	0.969	0.994	0.973	0.938
Xuchang	1.002	0.975	1.003	1	0.978	Xuchang	1.006	0.96	1	1.006	0.965
Luohe	1	0.955	1	1	0.955	Luohe	0.979	0.974	0.996	0.983	0.953
Sanmenxia	1	1.001	1	1	1.001	Sanmenxia	1.001	1.011	1	1.001	1.012
Nanyang	0.998	0.999	0.997	1.001	0.998	Nanyang	0.996	1.001	0.991	1.005	0.997
Shangqiu	1.017	0.967	1.017	1.001	0.983	Shangqiu	1.02	0.973	1	1.02	0.992
Xinyang	1.008	0.982	1.01	0.997	0.989	Xinyang	1	0.993	0.988	1.012	0.993
Zhoukou	1.002	0.999	1	1.002	1.001	Zhoukou	1	0.995	1	1	0.995
Zhumadian	1.018	0.989	1.015	1.003	1.007	Zhumadian	1.009	0.998	0.997	1.012	1.006
Jiyuan	1	0.99	1	1	0.99	Jiyuan	1.004	1.002	1	1.004	1.005
Changzhi	1	1.035	1	1	1.035	Changzhi	1.029	1.012	1	1.029	1.041
Jincheng	1	1.054	1	1	1.054	Jincheng	1.039	1.015	1	1.039	1.055
Yuncheng	1.01	1	1.009	1.001	1.01	Yuncheng	1.021	1.005	1.004	1.017	1.027
Liaocheng	0.978	0.985	0.976	1.002	0.963	Liaocheng	0.974	0.954	0.975	0.999	0.929
Heze	0.984	0.947	0.997	0.986	0.931	Heze	0.996	0.942	1	0.996	0.938
Huaibei	1.009	0.998	1.012	0.997	1.007	Huaibei	0.996	1.003	0.994	1.002	1
Bozhou	1	0.995	1	1	0.995	Bozhou	1.019	1.017	1	1.019	1.036
Suzhou	1.02	0.968	1	1.02	0.987	Suzhou	1.056	0.983	1	1.056	1.038
Bengbu	0.998	0.969	0.994	1.004	0.967	Bengbu	1.028	0.994	1	1.028	1.022
Fuyang	1.011	0.978	1.01	1.001	0.989	Fuyang	1.042	0.997	1	1.042	1.039
Xingtai	0.941	0.999	0.942	0.999	0.941	Xingtai	0.954	1.004	0.954	0.999	0.957
Handan	1.004	0.998	1.007	0.997	1.001	Handan	1	0.986	1	1	0.986

5.2 Development Suggestions

The manufacturing industry of the CPUA is currently in a state of being "large but not strong", with significant environmental factors impacting its efficiency. The TFP of the manufacturing industry is declining due to technological stagnation, whereas internal R&D expenditure and goods export volume are beneficial to manufacturing efficiency. Increased investment in basic research for the manufacturing industry is advised to enhance output or save on inputs. This also implies that R&D investment has not yet reached an optimal state. The government should expand its openness, promote the strong foundation project in the manufacturing sector, and facilitate the transformation and upgrading of traditional manufacturing and small and medium-sized enterprises. Relevant departments should focus on current core technologies, encourage the transformation of achievements, develop intelligent manufacturing, and strengthen future technology R&D reserves [25]. Furthermore, there are significant disparities in the high-quality development level of manufacturing across regions in the CPUA. It is suggested to leverage the radiating effect: cities lagging in high-quality manufacturing development, such as Pingdingshan, Zhumadian, Puyang, Bengbu, Sanmenxia, Xingtai, Huaibei, Fuyang, Changzhi, Xinyang, Hebi, Yuncheng, Suzhou, Jincheng, Bozhou, and Jiyuan, should strengthen cooperation with cities that are better developed in manufacturing, such as Zhengzhou, Luoyang, Anyang, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Nanyang, Zhoukou, Zhumadian, Liaocheng, and Handan. This strategy aims to break regional barriers, integrate resources, divide labor, and innovate collaboratively to form a strong manufacturing cluster ecosystem. Additionally, both insufficient input and redundancy can lead to low SE. Cities with inadequate manufacturing input should vigorously develop capital markets to ensure a stable supply of investment funds and appropriately build enterprise numbers [26]. For areas with input redundancy, improving the quality of manufacturing inputs and accelerating the green transformation of manufacturing is essential.

Based on the calculation results of the three efficiencies, there is significant differentiation between cities. To better promote high-quality development in the CPUA's manufacturing industry, specific improvement measures or development strategies are proposed for cities with low SE, low TE, both low technical and scale efficiencies, and both high TE and SE. Additionally, it was found that PTE was relatively stable and good from 2017 to 2022, with cities having low PTE also experiencing low SE. Therefore, cities with low PTE are discussed together with those having both poor pure TE and SE.

(1) For areas with low manufacturing SE, such as Jiaozuo, Xuchang, Luohe, Jiyuan, Changzhi, Jincheng, Yuncheng, Bozhou, Suzhou, Bengbu, and Fuyang, optimization of capital and other inputs can be implemented. Focusing on a sub-industry within the manufacturing sector to develop it into a specialty industry within the province, the CPUA, or even nationally is recommended. Bengbu City, which is most affected by environmental factors and random errors, should focus on improving external conditions, such as increasing R&D internal funding and goods import volume.

(2) For areas with overall low manufacturing efficiency, a comprehensive improvement is needed. Cities like Kaifeng, Luoyang, Anyang, Hebi, Xinxiang, Puyang, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhumadian, Huaibei, Pingdingshan, Xingtai, and Handan, which have been underperforming in both manufacturing SE and TE from 2017 to 2022, indicate a lack of stability in manufacturing scale investment, insufficient innovation capacity, and inadequate introduction of advanced technology. Efforts should be made to vigorously develop the capital market to ensure stable funding for manufacturing, actively introduce advanced technology, enhance the independent innovation ability of enterprises, and drive the development mechanism of the manufacturing industry. Cities can also transform and upgrade their manufacturing industries, restructure the industrial value chain, introduce professional talent to transform traditional manufacturing sectors, and stimulate the innovative vitality of talent to enhance the core competitiveness of traditional manufacturing industries. This will advance the "clustered" development of the manufacturing industry in the CPUA, creating a strong manufacturing cluster ecosystem [27].

(3) For areas with generally high manufacturing efficiency or overall good performance, development should focus on specialty manufacturing. Cities like Zhengzhou, Zhoukou, Liaocheng, and Heze can rely on their advantages in both manufacturing inputs and outputs [28]. They should engage in comprehensive exchanges and cooperation, accelerate foreign trade, increase city promotion efforts, improve the scientific and technological innovation system, strengthen key core technological research, advance intelligent manufacturing, and expedite the green transformation of the manufacturing industry. Efforts should be made to build the local industry into a national specialty industry, promoting high-quality development of both the manufacturing industry and the economy in the CPUA.

5.3 Outlook

This paper employs the three-stage DEA model and Malmquist index method for a systematic analysis of the high-quality development efficiency of the manufacturing industry in the CPUA. Generally, the empirical research has achieved the expected results, but there are still areas worthy of further exploration.

(1) Limited Collection of Indicator Data: There is no standard definition for indicators evaluating the high-quality development efficiency of the manufacturing industry in statistical yearbooks, making it difficult to collect data corresponding to each evaluation indicator. This paper, synthesizing the research findings of many scholars, will continue to pay attention to updates in related concepts, definitions, and data to seek more typical data sources.

(2) Limited Scope of Research Subjects: The data used for comparative analysis in this paper is limited to the CPUA and the manufacturing industry's high-quality development efficiency in 31 provincial-level administrative regions on the Chinese mainland from 2017 to 2022. It does not compare the CPUA with every other urban agglomeration in the country individually. Comparison with other cities and the issues that arise are also worth deeper discussion.

(3) Limited Selection of Environmental Factors: Given the wide range of manufacturing industry data and numerous environmental influencing factors, this paper could not consider all aspects comprehensively. It selected relevant environmental factors based on a summary of numerous scholars' research results and the current state of the manufacturing industry in the CPUA. Future studies will continue to analyze the effects of different environmental indicators on the high-quality development efficiency of the manufacturing industry in the CPUA.

5.3.1 Theoretical significance

The high-quality development efficiency of the manufacturing industry has always been a hot topic among scholars, with extensive research success. This paper uses the three-stage DEA and three-stage DEA-Malmquist methods to measure the efficiency and total factor productivity changes in the CPUA, combining static and dynamic analysis to more comprehensively and accurately reflect the high-quality development efficiency of the CPUA. The paper optimizes the environmental variable indicators when excluding the impact of exogenous environmental variables and random errors, making the measurement results more convincing.

5.3.2 Practical significance

By measuring the high-quality development efficiency of the manufacturing industry in the CPUA and analyzing factors affecting efficiency, this paper provides references for the government to assess the level of manufacturing development, adjust economic policies, and propose more reasonable manufacturing development plans. It aims to provide a basis for improving the economic operation capabilities of the manufacturing industry and achieving high-quality development. Additionally, the research results on the high-quality development efficiency of the manufacturing industry in the CPUA have strong representativeness in the entire history of urban development and can serve as a reference for improving the development status of other regions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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