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Assessing Logistics Industry Efficiency and Identifying Determinants in Shijiazhuang, China – A Comprehensive Analysis

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ABSTRACT

This study evaluated the efficiency of the logistics industry in Shijiazhuang City by using the DEA-BCC and Malmquist index models to analyse efficiency changes from 2010 to 2019 and compared them with seven logistics hub cities in the eastern region. The results indicate that Shijiazhuang's logistics efficiency is high, with leading technology and management levels in the eastern region. Additionally, the Tobit regression model was used to explore factors affecting Shijiazhuang's logistics efficiency, finding that economic development and locational advantages positively influence logistics efficiency, whereas industrial structure has a negative impact. Based on these findings, it is recommended that Shijiazhuang City enhance its logistics efficiency by improving logistics infrastructure, developing multimodal transport, leveraging locational advantages, elevating economic levels and openness, advancing logistics informatisation and nurturing high-quality logistics talent.

KEYWORDS

logistics efficiency; DEA model; influencing factors; tobit regression.

1. INTRODUCTION

The logistics sector is integral to the sustained economic development of nations, acting as a barometer of a country's overall economic strength and modernisation. In China, facing economic slowdown pressures, the logistics industry has emerged as a pivotal growth driver, essential for fostering new economic momentum. This study focuses on Shijiazhuang, a key city in the Bohai Economic Rim and Hebei Province's political, economic, technological, financial, cultural and information hub. Shijiazhuang's strategic location within the Jing-Jin-Ji region, coupled with its advanced transportation and aviation infrastructure, has positioned it as a national logistics hub.

Despite the rapid growth and policy support, gaps remain in understanding the specific efficiency levels of Shijiazhuang's logistics industry and the factors influencing it. This paper seeks to fill these gaps by providing a detailed evaluation of the logistics efficiency in Shijiazhuang from 2010 to 2019. The study employs the DEA-BCC and Malmquist index models to assess efficiency changes and compares these with seven prominent logistics hub cities in the eastern region of China. Additionally, the Tobit regression model is utilised to identify determinants of logistics efficiency, focusing on economic development, locational advantages and industrial structure.

The research aims to address the following questions:

1) What is the current efficiency level of Shijiazhuang's logistics industry compared to other logistics hubs in the eastern region?
2) What are the key factors influencing the logistics efficiency in Shijiazhuang?
3) How can Shijiazhuang enhance its logistics efficiency based on the identified factors?

The innovations presented in this article include the use of comprehensive models to assess logistics efficiency over a decade and the identification of specific determinants that influence this efficiency. The findings provide actionable recommendations for policymakers and industry stakeholders to enhance logistics efficiency through targeted interventions.

By addressing these research questions and presenting novel insights, this study contributes to the existing literature on logistics efficiency and offers practical implications for enhancing the logistics sector in Shijiazhuang, thereby supporting broader economic development goals.

2. LITERATURE REVIEW

2.1 Research methodology for logistics efficiency evaluation

Data Envelopment Analysis (DEA) is widely recognised for its capability to evaluate efficiency without needing to construct a specific function, manually set weights or consider data quantification, resulting in more objective outcomes. Consequently, it has become the preferred method for efficiency studies. Internationally, scholars have adopted the DEA model earlier than their domestic counterparts, with a focus primarily on the micro level (specific logistics companies or segments) rather than the macro level (specific regions or the entire industry). Merkert and Hensher utilised a two-stage DEA model to evaluate the efficiency of 58 airlines and applied a Tobit regression model to analyse factors influencing airline efficiency, revealing that new aircraft types impact cost efficiency but not technical efficiency [1]. Ichinose and Yamamoto developed DEA-BCC and DEA-CCR models to examine the logistics efficiency of solid waste in Japan, considering constant and variable returns to scale [2]. Similarly, Wanke calculated the logistics efficiency of Brazilian container and bulk ports using a two-stage DEA model, identifying key factors affecting port logistics efficiency [3]. Park et al. assessed the efficiency of 14 Korean logistics providers using a DEA model, both dynamically and statically, and subsequently ranked them [4]. Angelos et al. analysed the efficiency of 30 international airlines from 2012 to 2016 using the SE-DEA model, indicating that the US airlines' efficiency was lower than that of Euro-Asian airlines [5]. Zarbi and Shin applied the DEA model to measure the efficiency of Iranian ports during a decade of sanctions, finding an overall decline in port efficiency [6].

These studies demonstrate that the adoption of DEA methodologies across various regions and sectors effectively provides objective efficiency assessments. This widespread application underscores the importance of using DEA for evaluating logistics efficiency in diverse contexts.

2.2 Logistics efficiency evaluation indicators

The absence of a unified concept of the logistics industry within academia has led scholars to develop diverse efficiency evaluation indicators. Internationally, Panayides reviewed the efficiency of seaports using the DEA model, summarising primary input indicators as the number of ships and berths, and output indicators as port throughput and customer satisfaction [7]. Markovits compared the logistics efficiency of 29 European countries in 2011 using the PC-DEA model, with input indicators including highway mileage, railway mileage, per capita GDP and wages in the transportation and warehousing industry, with output indicators being railway and road transport volumes [8]. Andrejić estimated the logistics efficiency of eight European countries using the PC-DEA model and ranked them. The input indicators included infrastructure, international transport costs, customs speed and export costs; the output indicators were logistics service quality, timeliness and shipping quality [9]. Nam Kyu Park et al. assessed and ranked the efficiency of 30 major ports in China and Korea in 2014 using the DEA model, finding Korean ports' efficiency significantly lower than that of Chinese ports. The input indicators were berth length, yard area, number of quay and yard cranes; the output indicator was container throughput [10]. Marchetti and Wanke evaluated the efficiency of Brazilian railway logistics from 2010 to 2014 using a two-stage DEA model, with employee numbers and freight cars as input indicators and transport volume as the output indicator [11].

These studies highlight the variability in input and output indicators used for evaluating logistics efficiency across different contexts and regions. This variability underscores the complexity of measuring logistics efficiency and the need for tailored approaches depending on specific logistical and regional characteristics.

2.3 Factors affecting logistics efficiency

The selection of factors influencing logistics efficiency varies between micro and macro perspectives due to differing research focuses. Internationally, Cullinane and Ji analysed the efficiency of container ports using the DEA model and concluded that port privatisation enhances container port efficiency [12]. Merkert R used a two-stage DEA model and Tobit regression to identify that route optimisation impacts technical efficiency, while introducing new aircraft affects cost efficiency [1]. Felício et al. evaluated the efficiency of 12 container terminals in Portugal and Spain, identifying regional and continental location, as well as maritime and land channels, as influencing factors [13]. Daniel Y. Lee summarised common factors affecting logistics efficiency in China, Japan and Korea, such as government industrial policy, infrastructure condition, communication network setup and the third-party logistics market [14]. Hong S and Zhang A established a DEA-LPI model to calculate the logistics efficiency of 141 countries, concluding that geographical location and income level influence logistics efficiency [15].

These studies reveal that the factors influencing logistics efficiency are complex and vary significantly across different regions and sectors. Key determinants include infrastructure development, government policies, technological advancements, as well as geographical and economic conditions.

2.4 Literature review summary

This literature review synthesises existing research on logistics efficiency evaluation, highlighting the predominant use of the DEA method and its variants (two-stage DEA, three-stage DEA, SE-DEA, DEA-Malmquist models) to assess logistics efficiency at both micro and macro levels. Input indicators commonly include berth numbers, crane numbers, employee numbers and wages, while output indicators focus on throughput and freight volume. Factors such as privatisation level, infrastructure status and freight income significantly impact logistics efficiency. However, research on Shijiazhuang's logistics efficiency has been largely qualitative. This study aims to fill this gap by evaluating Shijiazhuang's logistics efficiency from 2010 to 2019 using a DEA model with specific input-output indicators and employing Tobit regression to analyse the impact of selected factors, providing actionable recommendations based on the findings.

3. METHODOLOGY

DEA assesses decision units by ascertaining whether they operate on the production frontier, enabling a comprehensive efficiency comparison. A. Charnes, W.W. Cooper and E. Rhodes introduced the Data Envelopment Analysis (DEA) method, a mathematical technique that combines a linear programming model based on advanced mathematics with the marginal efficiency theory from econometrics.

The efficiency evaluation model outlined in this paper comprises two key components. Firstly, utilising the DEA-BCC model entails a cross-sectional assessment of the relative efficiency of ten inland river ports, including Nanjing Port, in 2019. Secondly, it encompasses an in-depth examination of the adequacy of port development levels, achieved by combining entropy-weighted TOPSIS with the results obtained from the DEA model calculations.

3.1 Data envelopment analysis

BCC-DEA model

Banker and other scholars put forward the BCC model based on variable returns to scale. The difference between the BCC model and the CCR model lies in whether there are constraints in the dual linear programming model.

$\sum_{j=1}^{b} \lambda_j = 1$, BCC model is as follows:

$$Min\ \ \theta$$

$$s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j X_j + s^- = \theta X_0 \\ \sum_{j=1}^{n} \lambda_j Y_j - s^- = Y_0 \\ \sum_{j=1}^{b} \lambda_j = 1 \\ \lambda_j \geq 0, \qquad (j = 1,2,\cdots,n) \\ s^+ \geq 0, s^- \geq 0, \theta \in R \end{cases} \tag{1}$$

Let the optimal solution of (1) be $\lambda^*, \theta^*, s^{*+}$and s^{*-}, in which case:

① When $\theta^* = 1$, $s^{*+} = 0$, $s^{*-} = 0$, DMU efficiency is DEA effective;

② When $\theta^* = 1$, $s^{*+} \neq 0$, $s^{*-} \neq 0$, DMU is DEA weakly efficient;

$0 \leq \theta^* \leq 1$ when the DMU is DEA, it is invalid.

Given the rarity of constant returns to scale in the social production process, where output factors are more challenging to control than input factors, the BCC model, which accounts for variable returns to scale, proves more suitable for time-series data analysis than other DEA models. Hence, this study adopts an input-oriented BCC model to evaluate the efficiency of Shijiazhuang and seven cities in the eastern region over a decade.

Dynamic analysis Malmquist exponential model

The BCC model captures the efficiency of Decision Making Units (DMUs) at a specific time but does not reflect changes in efficiency over a period. To address this, the Malmquist index model is introduced for dynamic analysis of the efficiency variation of DMUs, identifying the reasons for changes in efficiency.

When the technology level remains constant in period t, let $D^t(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ represent the distance functions for each DMU during periods t and t+1, respectively. Conversely, when the input-output remains unchanged in period t, let $D^{t+1}(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ represent the distance functions for each decision-making unit (DMU) in periods t and $t+1$, respectively. The formula for the Malmquist Index (Total et al.) is as follows:

$$TFPCH = M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \times \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right]^{\frac{1}{2}} \tag{2}$$

When returns to scale are constant, the Malmquist Index can be decomposed as follows:

$$TFPCH = EFFCH \times TECH = PECH \times SECH \times TECH \tag{3}$$

The meanings of each decomposed part are shown in *Table 1*:

Table 1 – Malmquist index and decomposition meaning

Abridge	Name	Meaning when greater than 1	Meaning at less than 1
TFPCH	Total factor productivity	Total factor productivity has increased	Total factor productivity has decreased
TECH	Technology	Technical progress	Technical regression
EFFCH	Technical efficiency	Technological efficiency improvement	Reduced technical efficiency
PECH	Pure technical efficiency	The technology application level has been improved	The level of technology application has decreased
SECH	Scale efficiency	Scale optimisation	Scale deterioration

Selection of efficiency evaluation indicators

Based on relevant principles and literature, and considering the disparities in statistical data among provincial capital cities in Eastern China, this study adopts the number of employees in the logistics sector and the fixed asset investment in logistics as input indicators. The output indicators are represented by the added value of the logistics sector and the freight volume. Furthermore, it is essential to note that the logistics industry needs to be distinctly categorised within China's national economic industry classification. Scholars typically use transportation, warehousing and postal services to represent the logistics industry. Additionally, statistical yearbooks reveal that the output value of transportation, warehousing and postal services constitutes a significant proportion of the logistics industry. Therefore, this paper represents the logistics industry through transportation, warehousing and postal services. The evaluation index system for this study is presented in *Table 2*:

Table 2 – Evaluation index system of Logistics efficiency in Shijiazhuang city

Indicator type	**Name of index**	**Indicator code**
Investment index	Transportation, storage and postal workers (ten thousand employees)	X1
	Fixed assets investment in transportation, storage and postal services (100 million yuan)	X2
Output indicators	Freight volume (ten thousand tons)	Y1
	Add value of transportation, storage and postal service (100 million yuan)	Y2

3.2 Tobit regression model

Introduction to Tobit regression models

Given that the efficiency values calculated by the DEA model range between 0 and 1, which meets the applicability criteria for the Tobit regression model, this study employs the Tobit regression model to analyse the factors affecting efficiency in Shijiazhuang, China. The Tobit model is outlined as follows:

$$Y = \begin{cases} Y^* = \beta X + \varepsilon & ,Y^* > 0 \\ 0 & ,Y^* \leq 0 \end{cases} \tag{4}$$

where the explained variable is Y, Y^* is the truncated dependent variable, ε is the random error, β is the regression coefficient, and X is the independent variable.

Selection and quantification of factors affecting logistics industry efficiency

The contemporary logistics sector, a multifaceted industry encompassing various fields and departments, is influenced by macroeconomic conditions, micro-industry factors and corporate dynamics. This study synthesises prior research and Shijiazhuang's specific context to identify six critical determinants of logistics efficiency: economic development level, openness degree, locational advantages, industrial structure, logistics facility utilisation rate and informatisation level of logistics.

1) Economic Development Level (GDP): The growth of Shijiazhuang's logistics is tied to substantial consumer, investment and demand, necessitating a thriving regional economy. Hence, this paper selects Shijiazhuang's GDP as a quantitative measure of economic advancement.
2) Openness Degree (OD): The scale and volume of foreign investment denote a region's openness, initially boosting economic growth and, subsequently, the logistics sector. This study uses foreign investment amounts, converted based on the current exchange rate, to quantify Shijiazhuang's openness.
3) Locational Advantage (LQ): A region's economic status, geographical location and policy environment constitute its locational advantage, positively affecting logistics. The locational quotient, indicating the logistics industry's GDP ratio against the national level, measures this advantage.
4) Industrial Structure (IS): The proportion of the three major sectors, with logistics supporting and supported by the tertiary sector, outlines the industrial structure. The paper quantifies this by comparing the tertiary sector's output to Shijiazhuang's total GDP.
5) Logistics Infrastructure Utilisation Rate (LF): The efficiency of the logistics infrastructure utilisation reflects the effective use of logistics resources in Shijiazhuang, promoting efficiency. Given the minimal share of air and rail freight, this study adopts the ratio of road freight volume to road mileage as a proxy.
6) Logistics Informatisation Level (LI): The rise of the internet economy's rise escalates the demand for logistics services and propels the sector's growth. This paper measures informatisation through Shijiazhuang's telecommunication volume.

4. RESULTS

4.1 DEA efficiency analysis

This study employs the DEA-BCC model and the Malmquist Productivity Index to assess the efficiency of logistics in Shijiazhuang City, analysing each year as a Decision Making Unit (DMU) both statically and dynamically, vertically and horizontally. Given the necessity for a prolonged series to study the development trends within an industry accurately. In this academic examination of logistics efficiency within Shijiazhuang, Hebei Province, China, the selection of data from 2010 to 2019 is a deliberate methodological choice. The advent of the COVID-19 pandemic in 2020 introduced significant disruptions across global economic and logistical landscapes, rendering post-2020 data less indicative of baseline logistics performance. Consequently, this analysis leverages a decade's worth of data prior to the pandemic, aiming to provide an undistorted view of Shijiazhuang's logistics efficiency. This period offers a solid foundation for understanding pre-pandemic logistics operations, which is crucial for establishing benchmarks and evaluating future logistics efficiency trajectories amidst and beyond global health crises.

Table 3 – Shijiazhuang City 2010–2019 Logistics Efficiency Evaluation Results

Decision-making units	Overall efficiency	Pure technical efficiency	Efficiency of scale	Economies of scale
2010	0.808	1.000	0.808	↑
2011	0.875	0.974	0.899	↑
2012	1.000	1.000	1.000	–
2013	0.963	0.987	0.975	↓
2014	0.764	0.799	0.956	↓
2015	0.832	0.886	0.939	↓
2016	0.949	1.000	0.949	↓
2017	1.000	1.000	1.000	–
2018	1.000	1.000	1.000	–
2019	1.000	1.000	1.000	–
Mean value	0.919	0.965	0.953	

Data sources: DEAP2.1

The reference objects for this study were selected from seven provincial capitals and municipalities in the eastern region of China, namely Beijing, Tianjin, Jinan, Nanjing, Shanghai, Hangzhou and Guangzhou. These cities are located in China's most economically advanced eastern region and also serve as national logistics hub cities, aligning with Shijiazhuang's development positioning. Among these cities, Beijing, Tianjin and Shanghai are municipalities directly under the central government, while the rest are provincial capitals. These cities share similar locational conditions with Shijiazhuang and have higher economic volumes. Hence, these seven cities were chosen as horizontal reference objects to identify issues in Shijiazhuang's logistics efficiency better. To ensure comparability in efficiency evaluation, the logistics efficiency indicators for these seven cities utilise the same evaluation system as that of Shijiazhuang.

Vertical comparison of logistics efficiency

This section employs the DEAP 2.1 software and adopts the input-oriented DEA-BCC model to evaluate the efficiency of the logistics industry in Shijiazhuang City from 2010 to 2019. By selecting ten decision-making units, two input indicators and two output indicators, the comprehensive efficiency, pure technical efficiency and scale efficiency of the logistics in Shijiazhuang City are calculated, with the results as follows.

Table 4 – Results of input-output redundancy analysis in Shijiazhuang City from 2010 to 2019

Time	Practitioners (ten thousand people)	Fixed assets investment (RMB 100 million yuan)	Freight volume (ten thousand tons)	Value (100 million yuan)
2010	0	0	0	0
2011	0.154	5.474	512.125	
2012	0	0	0	0
2013	0.085	3.546	0	23.277
2014	1.610	60.645	8115.515	0
2015	0.864	39.775	9217.375	0
2016	0	0	0	0
2017	0	0	0	0
2018	0	0	0	0
2019	0	0	0	0

Data sources: DEAP 2.1

Between 2010 and 2019, Shijiazhuang's logistics sector showcased notable efficiency, with an average comprehensive efficiency of 0.919, pure technical efficiency at 0.965 and scale efficiency at 0.953, indicating a growth in returns to scale.

1) Comprehensive efficiency analysis of Shijiazhuang City, 2010–2019

During this period, we witnessed significant fluctuations in logistics efficiency, with four years achieving optimal DEA scores of 1, suggesting full utilisation of resources. However, six years recorded efficiencies below 1, highlighting the potential for improvement. The analysis reveals three distinct trends: an initial rise from 2010 to 2012, a dip between 2013 and 2016, with the lowest point in 2014, followed by a consistent high from 2017 to 2019. The early increase is attributed to the post-2008 economic recovery boosting logistics demand. The subsequent decline was mainly due to environmental challenges, prompting a shift towards green logistics. The final period of sustained high efficiency underscores Shijiazhuang's strategic transformations towards intelligent logistics and the benefits of being a key city in the Integration of Beijing, Tianjin and Hebei plan and a national transportation hub, leveraging advanced logistics talents and intelligent technologies.

2) Pure technical and scale efficiency analysis of Shijiazhuang, 2010–2019

From 2010 to 2019, technical and scale efficiency analyses examined Shijiazhuang's logistics efficiency. The study utilised DEA methodology to chart the efficiency trends, revealing that while pure technical efficiency fluctuated more significantly, the overall efficiency trends aligned closely with it, and four years within this period recorded a pure technical efficiency below one, indicating inefficiencies in management, capabilities and technology. Enhancements in these areas are recommended to improve efficiency. Scale efficiency, which indicates the optimal scale of input to output, showed that returns to scale were increasing for six years, suggesting that inefficiencies were partly due to the small scale of operations.

3) Projection analysis of invalid units

Shijiazhuang's logistics from 2010 to 2019 was analysed, revealing six years of inefficiency. Using DEA (Data et al.), we identified the causes by examining input surpluses and output deficits. The analysis of the years 2010 and 2016 showed optimal use of resources, while other years suffered from inefficiencies due to excessive labour and capital inputs versus outputs. This inefficiency necessitates improved management, technology adoption and workforce training. It suggests a need for strategic investment focusing on quality and scale to enhance productivity. Recommendations include optimising workforce allocation and enhancing equipment and technology utilisation to prevent resource wastage. This analysis underscores the significance of aligning investment with output demands to maximise logistics efficiency in Shijiazhuang.

Cross-sectional comparison of logistics efficiency

1) Cross-sectional static comparative analysis of logistics efficiency

Evaluating Shijiazhuang's logistics efficiency from 2010 to 2019 reveals a composite efficiency score 0.919. This indicates a generally high efficiency over the decade, with diminishing and stable returns to scale. As a national logistics hub, Shijiazhuang's efficiency was compared horizontally with seven major eastern cities, including Beijing, Tianjin, Jinan, Nanjing, Shanghai, Hangzhou and Guangzhou, to identify gaps with other national logistics hubs. Considering similar location conditions and development strategies, this comparison employed the DEA-BCC model using DEAP2.1 software, focusing on two input indicators (employment and capital investment) and two output indicators (freight volume and added value). The calculation results showcased the relative standing of Shijiazhuang among these logistics centres. The results are shown in *Tables 5, 6 and 7*:

Table 5 – Comprehensive efficiency comparison of each city

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean value	Ranking
Shijiazhuang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Beijing	0.995	0.898	0.688	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.958	3
Tianjin	0.581	0.568	0.431	0.364	0.412	0.449	0.653	0.880	0.971	1.000	0.631	6
Jinan	1.000	1.000	1.000	1.000	1.000	1.000	0.960	0.819	0.909	0.991	0.968	2
Nankin	1.000	0.747	1.000	0.570	0.414	0.361	0.400	0.351	0.413	0.488	0.574	7
Shanghai	0.665	0.548	0.576	0.642	1.000	0.770	0.739	0.876	0.932	0.860	0.761	5
Hangzhou	1.000	0.472	0.712	0.422	0.464	0.514	0.627	0.600	0.425	0.452	0.569	8
Guangzhou	0.876	1.000	0.593	0.529	0.755	1.000	1.000	1.000	1.000	1.000	0.875	4

Data sources: DEAP 2.1

Table 6 – Pure technical efficiency comparison of each city

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean value	Ranking
Shijiazhuang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Tianjin	0.959	0.675	0.777	0.625	0.490	0.459	0.719	1.000	1.000	1.000	0.770	6
Jinan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.895	1.000	1.000	0.990	4
Nankin	1.000	0.778	1.000	0.888	0.470	0.436	0.502	0.454	0.522	0.525	0.587	8
Shanghai	1.000	0.619	1.000	1.000	1.000	0.772	0.751	0.890	0.934	1.000	0.897	5
Hangzhou	1.000	0.829	0.792	0.503	0.571	0.636	0.902	0.860	0.652	0.676	0.742	7
Guangzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1

Data sources: DEAP 2.1

Table 7 – Scale and efficiency comparison of each city

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Mean value	Ranking
Shijiazhuang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Beijing	0.995	0.898	0.688	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Tianjin	0.606	0.841	0.555	0.583	0.840	0.978	0.909	0.880	0.971	1.000	0.770	6
Jinan	1.000	1.000	1.000	1.000	1.000	1.000	0.960	0.915	0.909	0.991	0.990	4
Nankin	1.000	0.960	1.000	0.642	0.880	0.828	0.797	0.774	0.792	0.929	0.587	8
Shanghai	0.665	0.886	0.576	0.642	1.000	0.998	0.983	0.984	0.999	0.860	0.897	5
Hangzhou	1.000	0.570	0.899	0.839	0.812	0.808	0.695	0.697	0.652	0.669	0.742	7
Guangzhou	0.876	1.000	0.593	0.529	0.755	1.000	1.000	1.000	1.000	1.000	1.000	1

Data sources: DEAP 2.1

Through evaluating Shijiazhuang's logistics efficiency between 2010 and 2019, it was found that the city achieved an average comprehensive logistics efficiency of 1.000, placing it first among eight major eastern cities. This underscores Shijiazhuang's comparatively high logistics efficiency within this region over the past decade, which is especially notable as a pivotal national logistics hub. The analysis reveals that inland cities like Shijiazhuang, Beijing and Jinan, serving as inland port logistics hubs, outperform coastal cities' logistics efficiency, potentially due to the latter's less integrated multimodal transport systems.

Moreover, Shijiazhuang, Beijing and Guangzhou achieved the top rank in pure technical efficiency with a score of 1.000 across the decade, indicating their superior technological and management standards. Nevertheless, significant disparities were observed among the cities. Nanjing's pure technical efficiency has markedly declined since 2012, indicating challenges in addressing environmental issues and developing low-carbon and intelligent logistics.

Regarding scale efficiency, Shijiazhuang topped the list with a mean score of 1.000, suggesting that the city's logistics sector has effectively capitalised on its resources compared to its peers. The slight differences in scale efficiency across these cities suggest a generally optimal logistics scale in the eastern urban regions.

2) Cross-sectional dynamic comparative analysis of logistics efficiency

The preceding analysis used the DEA-BCC model to statically assess the logistics efficiency evolution within Shijiazhuang and seven eastern Chinese cities over the decade spanning 2010–2019. This part advances the investigation by applying the Malmquist index model to dynamically evaluate the shifts in logistics efficiency for the same geographic cohort. Calculations were performed using the Deap2.1 software, which facilitated a nuanced exploration of the efficiency dynamics, with the outcomes presented below:

Table 8 – Dynamic evaluation of logistics efficiency in Shijiazhuang City 2010–2019

Period	Technical efficiency	Technique	Pure technical efficiency	Scale efficiency	Total factor productivity
2010–2011	1.000	1.126	1.000	1.000	1.126
2011–2012	1.000	1.176	1.000	1.000	1.176
2012–2013	1.000	0.976	1.000	1.000	0.976
2013–2014	1.000	0.858	1.000	1.000	0.858
2014–2015	1.000	1.106	1.000	1.000	1.106
2015–2016	1.000	1.102	1.000	1.000	1.102
2016–2017	1.000	1.081	1.000	1.000	1.081
2017–2018	1.000	0.963	1.000	1.000	0.963
2018–2019	1.000	1.111	1.000	1.000	1.111

Data sources: DEAP 2.1

Reveals that Shijiazhuang's total factor productivity (TFP) witnessed increments in six specific intervals over a decade: from 2010-2011, 2011-2012, 2014-2015, 2015-2016, 2016-2017, to 2018-2019, signifying an advancement in the city's TFP during these periods. On the contrary, TFP declined during 2012-2013, 2013-2014, and 2017-2018, indicating periods of reduced productivity. A closer examination of Table 8 suggests that technological advancement is pivotal in determining the TFP levels in Shijiazhuang's logistics sector. Hence, prioritising technological development within the logistics industry is a critical strategy for Shijiazhuang.

Table 9 – Dynamic evaluation of logistics efficiency in 2010-2019 in eight cities in the eastern region

City	Technical efficiency	Technique	Pure technical efficiency	Scale efficiency	Total factor productivity
Shijiazhuang	1.000	1.051	1.000	1.000	1.051
Beijing	1.001	1.100	1.000	1.001	1.101
Tianjin	1.062	1.027	1.005	1.057	1.091
Jinan	0.999	1.057	1.000	0.999	1.056
Nankin	0.923	1.119	0.931	0.992	1.033
Shanghai	1.029	0.964	1.000	1.029	0.991
Hangzhou	0.916	0.991	0.957	0.956	0.907
Guangzhou	1.015	0.977	1.000	1.015	0.992
mean value	0.992	1.034	0.986	1.006	1.026

Data sources: DEAP 2.1

Over a decade, five cities among eight in China's eastern region, specifically Shijiazhuang, Beijing, Tianjin, Jinan and Nanjing, demonstrated Total Factor Productivity (TFP) above 1. This reflects enhancements in production efficiency, technological progression, and improved organisational and management standards. In contrast, Shanghai, Hangzhou and Guangzhou's TFPs below 1 suggest declining production levels, technological setbacks and a drop in organisational efficiency. Further analysis by using the $\mathrm{TFPCH} = \mathrm{EFFCH} \times \mathrm{TECH}$ formula reveals that technical efficiency remained stable at 1.000 in Shijiazhuang. In contrast, efficiency in Beijing, Tianjin, Shanghai and Guangzhou improved. Conversely, Jinan, Nanjing and Hangzhou saw a decline. Technological advancements were notable in Shijiazhuang, Beijing, Tianjin, Jinan and Nanjing, with the latter three cities outpacing Shijiazhuang. However, technology receded in Shanghai, Hangzhou and Guangzhou.

Further dissecting technical efficiency into pure and scale efficiencies, Tianjin excelled in pure technical efficiency, indicating logistic advancements. Meanwhile, Shijiazhuang Beijing, Shanghai and Guangzhou maintained consistent technical efficiency; Nanjing and Hangzhou regressed. Scale efficiency analysis highlighted Shijiazhuang's optimal logistics operation scale, with improvements seen in Beijing, Tianjin, Shanghai and Guangzhou. In contrast, Jinan, Nanjing and Hangzhou faced scale inefficiencies, indicating a decline in their logistic operations' scale over the decade.

Conclusion

This section presents an empirical analysis of the logistics efficiency in Shijiazhuang, utilising the DEA-BCC and Malmquist index models for assessment. Two inputs (logistics personnel and fixed asset investment) and two outputs (freight volume and logistics value added) were selected based on evaluation criteria and domestic research, forming an evaluation system tailored to Shijiazhuang. The DEAP2.1 software was used for static analysis of comprehensive, pure technical and scale efficiencies, alongside input redundancy analysis. A comparative static analysis was also conducted between Shijiazhuang and seven cities in the eastern region. The results reveal Shijiazhuang's logistics comprehensive efficiency average at 0.919, with a ten-year mean comprehensive efficiency at 1.000, indicating a positive overall logistics development trend. The inefficiency in some years resulted from purely technical and scale efficiencies; redundancy analysis showed inefficiencies primarily due to excess input of personnel and fixed assets against insufficient freight output, suggesting improvements through reasonable adjustments. Shijiazhuang's total factor productivity stood at 1.051, signifying rising logistics technical and managerial capabilities, primarily driven by technological progress.

4.2 Analysis of factors affecting logistics efficiency in Shijiazhuang

Data smoothness test

Given that this study utilises time series data, it is imperative to conduct a stationarity test to avert the issue of spurious regression. This research employs the software Stata16 to execute the Augmented Dickey-Fuller (ADF) test on the quantified results of influencing factors, with the findings as follows:

Table10 – ADF test results

Variable	△GDP	△2OD	△LQ	△IS.	△2LI	△2LF
T value	-6.385	-2.521	-5.002	-5.751	-2.242	-4.686
Critical value	-4.380	-4.380	-4.380	-4.380	-4.380	-4.380
Conspicuous level	0.000***	0.3177	0.002***	0.000***	0.4662	0.0007***

*Note: * * * represents a significant level of 1%, △ the first order difference and △ 2 the second order difference*

As indicated in *Table 10*, GDP, LQ and IS became stationary after first-order differencing. At the same time, LF reached stationarity following second-order differencing as per the unit root test. Conversely, OD and LI did not pass the stationarity analysis. When time-series data achieve stationarity after first or second-order differencing, it can be considered approximately stationary. Hence, the data in this study are stable, making it suitable for Tobit regression analysis.

Tobit regression results

According to the above-selected factors of logistics efficiency in Shijiazhuang, the Tobit regression model is constructed as follows:

$$TE_i = \beta_0 + \beta_1 GDP_i + \beta_2 OD_i + \beta_3 LQ_i + \beta_4 IS_i + \beta_5 LF_i + \beta_6 LI_i + \varepsilon \quad (5)$$

In this segment, we dissect the composite logistics efficiency of Shijiazhuang City in the i year denoted TE_i. This includes an examination of several critical economic indicators: GDP_i the Gross Domestic Product (GDP) for Shijiazhuang City in the year i; OD_i the volume of foreign investment in the city for the same period LQ_i, the locational quotient value for the year in question; IS_i the ratio of industrial structure; LF_i the utilisation rate of logistics infrastructure; and LI_i, the volume of postal and telecommunications services. The analysis also factors in an error term, represented as an unspecified variable, and a constant term, denoted by β_{0-6} indicating the regression coefficients for each influencing factor, i signifying the year of analysis. This study aims to elucidate the relationship between Shijiazhuang's comprehensive logistics efficiency and its economic and infrastructural dynamics, contributing insights towards optimising logistics performance in urban economic development （i = 2010, 2011, ⋯, 2019）.

Taking the comprehensive efficiency value of Shijiazhuang logistics as the dependent variable, economic development level, degree of opening, location advantage, industrial structure, utilisation rate of logistics infrastructure and logistics informatisation level as the independent variables, Tobit regression analyses were performed in this paper by using the Stata16 software. The regression results are shown in *Table 11*:

The regression analysis results are as follows:

1) The economic development of Shijiazhuang City, as measured by its gross domestic product (GDP), exhibits a strong positive correlation with the efficiency of its logistics sector. This relationship is quantitatively supported by a correlation coefficient 1.34e-08 and attains statistical significance at the 10% level. Such findings underscore the interplay between Shijiazhuang's economic growth and its logistics performance, wherein increased economic activity enhances societal demand for logistics and, in turn, fosters advancements within the logistics industry. This dynamic synergy significantly enhances logistics efficiency in Shijiazhuang, suggesting a virtuous cycle where economic development and logistics efficiency mutually reinforce each other.

2) The degree of globalisation (OD) positively correlates with Shijiazhuang City's logistics efficiency, as evidenced by a correlation coefficient of 0.000033. However, the significance level of 0.259 suggests a minimal influence of globalisation on the city's logistics efficiency. Notably, in 2018, foreign direct investment into Shijiazhuang amounted to 10.28 billion yuan, constituting 1.8% of the city's GDP. This data underscores the modest scale of foreign investment and its negligible direct contribution to the logistics sector, indicating that the city's logistic efficiency is marginally affected by its openness to international markets.
3) The locational advantage of Shijiazhuang city (LQ) exhibits a significant positive correlation with logistics efficiency, evidenced by a correlation coefficient of 1.504919, indicating a strong relationship and satisfying the 5% significance level. This relationship underscores the role of Shijiazhuang's geographical positioning in enhancing logistics efficiency. Due to two primary factors, the city's status as the pivotal hub in the Beijing-Tianjin-Hebei integration strategy is instrumental in this improvement. Firstly, Shijiazhuang benefits from favourable policies and a strategic position that attracts substantial logistics resources and deters their diversion. Secondly, the burgeoning demand within the logistics sector fosters a higher professional standard and operational efficiency. These elements collectively facilitate an environment conducive to advancing logistics efficiency in Shijiazhuang.
4) The industrial structure (IS) of Shijiazhuang city exhibits a negative correlation with its logistics efficiency, as evidenced by a correlation coefficient of -0.0544434 and a significance level of 0.008. This suggests that the share of the tertiary sector within the city's overall industrial composition significantly influences logistics efficiency. The underlying cause of this relationship is primarily due to the insufficient integrative development of the tertiary sector. Unlike expectations, expansion within this sector does not catalyse a corresponding rise in logistics demand. Concurrently, a reduction in the primary and secondary sectors, coupled with a sluggish growth in tangible goods demand, further constrains enhancements in logistics efficiency. This scenario underscores the necessity for a more symbiotic development among the industrial sectors to foster a conducive environment for logistics advancement.
5) The utilisation rate of the logistics infrastructure (LF) demonstrates a positive correlation with the efficiency of logistics operations. With a correlation coefficient of 0.1022887 and a significance level of 0.194, the positive relationship does not reach a high level of statistical significance. Over the last decade, enhancements in the utilisation rates of logistics infrastructure have not significantly contributed to the betterment of logistics efficiency. Given that the logistics infrastructure is currently operating at total capacity, there is a clear need for the strategic expansion of such infrastructure to support future efficiency improvements in logistics services. This study underscores the importance of scaling infrastructure with demand to sustain and enhance logistics performance.
6) The logistics informatisation (LI) level in Shijiazhuang city exhibits a weak negative correlation with its logistics efficiency, evidenced by a correlation coefficient of -2.92e-07 and a significance level of 0.674. This indicates that enhancements in the logistics informatisation level exert minimal influence on the city's logistics efficiency. The underlying reasons for this observation include the predominance of traditional logistics enterprises within Shijiazhuang, which characteristically exhibit low informatisation levels. Consequently, these enterprises lag in adopting the rapid advancements in intelligent logistics, big data, cloud computing and other informational technology sectors, hindering the positive impact of informatisation on logistics efficiency.

Conclusion

This section uses a Tobit regression model to present an empirical study on the factors affecting the efficiency of the logistics industry in Shijiazhuang City. The independent variable is the comprehensive efficiency value of Shijiazhuang City's logistics industry, with six factors as dependent variables. The findings reveal significant factors influencing the efficiency of the logistics industry in Shijiazhuang, including the level of economic development, industrial structure and location advantage. Specifically, the level of economic development and location advantage positively correlate with the efficiency of Shijiazhuang's logistics industry. In contrast, the industrial structure negatively correlates with logistics efficiency. Factors not significantly affecting Shijiazhuang's logistics efficiency are the degree of openness to the outside world, logistics infrastructure utilisation rate and logistics informatisation. Moreover, the degree of openness, logistics infrastructure utilisation rate and logistics informatisation have insignificant impacts on the efficiency of the logistics industry in Shijiazhuang.

Table 11 – Regression results of the factors affecting the logistics efficiency in Shijiazhuang city

Argument	Coefficient of correlation	Conspicuous level	Argument
△2GDP	1.34e-08	0.078*	△2GDP
△2OD	0.000033	0.259	△2OD
△LQ	1.504919	0.033**	△LQ
△IS	-0.0544434	0.008***	△IS
△2LF	0.1022887	0.194	△2LF

*Note: * * * indicates a significant level of 1%, * * indicates a significant level of 5% and * indicates a significant level of 10%*

5. CONCLUSIONS AND SUGGESTIONS

5.1 Research conclusion

This study investigates the logistics industry in Shijiazhuang City, focusing on two main aspects. First, suitable input and output indicators were selected based on the actual conditions in Shijiazhuang to construct an evaluation index system. The DEA model was then employed to assess the logistics efficiency of Shijiazhuang from 2010 to 2019. Second, the influencing factors of logistics efficiency in Shijiazhuang were identified and quantified based on the evaluation results, followed by an analysis using Tobit regression. Finally, suggestions for improving the logistics efficiency of Shijiazhuang were proposed based on the empirical analysis results. The conclusions are as follows:

1) Longitudinal analysis of logistics efficiency: The comprehensive logistics efficiency of Shijiazhuang from 2010 to 2019 was 0.919, indicating a good development status and a high level of logistics efficiency. In years where the comprehensive efficiency value was less than 1, it was due to the combined effects of pure technical efficiency and scale efficiency. Horizontally, the logistics efficiency of Shijiazhuang from 2010 to 2019 was higher than that of major cities in the eastern region such as Beijing, Tianjin, Jinan, Nanjing, Shanghai, Hangzhou and Guangzhou. Total factor productivity was also in an upward trend, primarily driven by technological progress.
2) Influencing factors: Economic development level, locational advantages and industrial structure significantly affect the logistics efficiency of Shijiazhuang. Economic development level and locational advantages positively correlate with logistics efficiency, whereas industrial structure has a negative correlation. The degree of openness, utilisation rate of logistics infrastructure and logistics informatisation level do not have a significant impact on logistics efficiency.
3) Scientific contributions: This study provides a comprehensive analysis of the logistics efficiency in Shijiazhuang using advanced quantitative methods such as DEA and Tobit regression models. The identification of key influencing factors offers a deeper understanding of the dynamics within the logistics sector, providing valuable insights for policymakers and industry stakeholders.

5.2 Suggestions for improving the efficiency of the logistics industry in Shijiazhuang

Based on the results of the previous empirical analyses of logistics efficiency and its influencing factors in Shijiazhuang City 2010–2019, and combined with the previous contents, this paper will put forward some suggestions to improve the level of logistics efficiency in Shijiazhuang City.

Improving logistics infrastructure and developing multimodal transport

The Tobit regression analysis indicates a positive correlation between the utilisation rate of logistics infrastructure and the efficiency of Shijiazhuang's logistics sector. Enhancing infrastructure utilisation is critical for boosting logistics efficiency. Shijiazhuang faces challenges such as inadequate facilities in logistics parks, leading to low enterprise settlement and industry aggregation, and an over-reliance on road freight. Recommendations include upgrading logistics park facilities, promoting enterprise settlement through strategic planning and incentives, and diversifying transportation modes by integrating road, rail and air transport to establish an efficient intermodal network.

Utilising the advantages of location to enhance industrial linkages

As a national logistics hub and a core city in the Jing-Jin-Ji region, Shijiazhuang boasts geographical advantages and resources in talent, information and education, fostering logistics development. Leveraging these advantages to support innovative logistics enterprises and enhancing inter-provincial connectivity can boost efficiency. Adjusting the industrial mix to bolster demand for logistics services, encouraging logistics outsourcing and promoting internal industry collaboration can enhance service capabilities and technological advancement in logistics.

Upgrading economic development and open up to foreign investment

Economic growth in Shijiazhuang has created a favourable environment for the logistics sector, showing a positive correlation with logistics efficiency. However, the impact of foreign investment remains minimal, suggesting the need for targeted government policies to attract foreign investment. Recommendations include leveraging economic development to improve the market environment for logistics and implementing tax and land incentives to attract foreign investment, addressing the shortfall in external funding.

Promoting logistics informatisation and high-quality talent development

Enhancing logistics informatisation can increase the speed of information transmission, improving logistics system efficiency. However, current levels of informatisation may hinder further efficiency improvements, indicating a need to accelerate innovative logistics initiatives. Recommendations include enhancing information exchange among logistics enterprises, offering high-quality information services and focusing on training top-tier logistics professionals. Collaborations with universities to cultivate skilled talent and attractive policies to draw external logistics talents are essential for fostering growth and efficiency in the logistics sector.

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中国石家庄的物流业效率评估与确定决定因素：综合分析

摘要：

本研究采用 DEA-BCC 和 Malmquist 指数模型，分析 2010-2019 年的效率变化，评价了石家庄市物流效率，并与东部地区 7 个物流中心城市进行了比较。结果表明，石家庄市的物流效率较高，在东部地区具有领先的技术和管理水平。此外，采用 Tobit 回归模型探讨了影响石家庄市物流效率的因素，发现经济发展和区位优势对物流效率有积极影响，而对产业结构有负面影响。基于这些发现，建议石家庄城市通过改善物流基础设施、发展多式联运、利用区位优势、提高经济水平和开放性、推进物流信息化、培养高素质物流人才等方式来提高物流效率。

关键词：

物流效率、DEA 模型、影响因素、Tobit 回归