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https://www.emerald.com/insight/1738-2122.htm

Received 13 March 2024
Revised 18 July 2024
23 September 2024
Accepted 2 October 2024

Regional efficiency analysis of fresh food cold chain logistics in China based on three-stage DEA model

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Abstract

Purpose – Assessing the efficiency of fresh food cold chain logistics as accurately as possible is essential for industry development planning. This study was designed to analyze the efficiency of fresh food cold chain logistics in China.

Design/methodology/approach – A three-stage data envelopment analysis (DEA) model was used to analyze the efficiency of fresh food cold chain logistics in 30 provinces of China from 2013 to 2019. The stochastic frontier analysis (SFA) model in the second stage was used to eliminate the influence of external environmental factors and random disturbances on efficiency analysis results.

Findings – (1) The overall actual efficiency of fresh food cold chain logistics in China is unsatisfactory, with an average technical efficiency of 0.382 over the 7-year period. (2) The national average technical efficiency and average scale efficiency were overestimated by 29.9% and 40.0%, respectively, compared with the actual values. (3) The efficiency of fresh food cold chain logistics does not align with the level of regional economic development. (4) Distinct regional variations exist in the efficiency of fresh food cold chain logistics in China, with higher efficiencies observed in Northwest China and the Central Yangtze River regions, and the lowest efficiencies in the northeast regions.

Originality/value – This study applies a three-stage DEA model to assess the development and regional differences of fresh food cold chain logistics in China, enriching the application of models and empirical analysis in this field. By analyzing the situation in China, it provides ideas and references for other developing countries to develop cold chain logistics.

Keywords Efficiency, Fresh food, Cold chain logistics, Three-stage DEA

Paper type Research paper

1. Introduction

As consumer demand for safe and high-quality items, particularly fresh foods, increases, so does the need for cold chain logistics (Trienekens *et al.*, 2012). According to the China Cold Chain Logistics Development Report (2022), China's total demand for food cold chain logistics reached 302 million tons in 2021, showing a 13.96% rise over the previous year. The market size for China's cold chain logistics reached 458.60 billion yuan in 2021, indicating substantial growth and rapid development in the cold chain logistics industry. Even so, China's fresh food cold chain logistics still faces many challenges.

This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2021-KA161726).

Journal of International Logistics and Trade
Vol. 22 No. 4, 2024
pp. 158-180
Emerald Publishing Limited
e-ISSN: 2508-7592
p-ISSN: 1738-2122
DOI 10.1108/JILT-02-2024-0009

The fresh food supply chain is intricate, posing challenges to the efficient development of cold chain logistics. Factors such as moisture evaporation, cellular respiration leading to spoilage and nutrient loss (Amorim and Almada-Lobo, 2014; Han *et al.*, 2021) and participation of various intermediaries (farmers, wholesalers, distributors, supermarkets, etc.) make appropriate refrigerated transport conditions critical for fresh food preservation (Zhao *et al.*, 2018; Raut *et al.*, 2019). Compared with typical developed countries (e.g. the United States, Canada, Japan, etc.), China still has problems such as resource wastage, inadequate infrastructure, low levels of specialization, and underdeveloped policies and standards (Zhao *et al.*, 2018; Han *et al.*, 2021). Due to the uneven distribution of economic development, population distribution and food production in different regions, the development degree of China's cold chain logistics varies greatly among regions (Dong *et al.*, 2020; He *et al.*, 2024). Similarly, developing countries such as Thailand, India and Malaysia, which have substantial agricultural product sectors, have similar issues in their cold chain logistics industries (Abu Hassan *et al.*, 2021; Ortiz-Gonzalo *et al.*, 2021; Kumar and Agrawal, 2023). Analyzing the development of cold chain logistics in China can provide a reference for these countries.

To achieve sustainable growth in the fresh food cold chain logistics industry, enhanced economic efficiency is imperative (Wang *et al.*, 2022). To do this, it is necessary to first identify the level of efficiency and the factors that affect it. The results are then used to make recommendations for improving efficiency accordingly. There are many widely used models for measuring economic efficiency, such as data envelopment analysis (DEA) (Solow, 1957; Charnes *et al.*, 1978), stochastic frontier analysis (SFA) (Aigner *et al.*, 1977), total factor productivity (TFP) (Solow, 1957), and so on. DEA is nonparametric but does not account for random errors. SFA is parametric and requires assumptions about the form of the production function. The three-stage DEA model combines DEA and SFA, which can eliminate the influence of environmental factors and stochastic errors to obtain more realistic efficiency values.

Therefore, this study calculated the relative economic efficiency of fresh food cold chain logistics in 30 provinces of China from 2013 to 2019 by applying a three-stage DEA model. In the second stage of DEA, this study analyzed the impact of environmental variables on efficiency. After removing external influences, the study compared the actual efficiency of different regions, made recommendations for improving efficiency and provided a reference for other developing countries.

The remainder of this study is presented below. Section 2 reviews the literature on research on the fresh food cold chain and the application of DEA methods in cold chain logistics. Section 3 describes the methodology. Section 4 describes the data set and the selected indicators. Section 5 shows the obtained computational results and the analytical discussion of them. Section 6 presents the main conclusions of the study.

2. Literature review

2.1 Fresh food cold chain logistics

Cold chain logistics can be understood as logistics activities that take place under refrigerated and frozen conditions. Cold chain can provide a suitable temperature and moderate environment for the production, processing, storage and transportation of fresh food products (Ren *et al.*, 2022). This aspect of cold chain logistics activities is fresh food cold chain logistics. In the fresh food cold chain logistics area, many scholars have focused their research on the analysis of influencing factors, the use of technology and supply chain operations in cold chain logistics. By using case studies and combining methods and techniques with practical applications, they focus more on achieving the cold chain transport process for agricultural products. Kuo and Chen (2010) proposed a logistics service model based on a multi-temperature joint distribution system. Amorim and Almada-Lobo (2014) constructed a model to maximize the freshness of fresh food and minimize distribution costs. Using a ribonucleic acid-ant colony optimization algorithm, Zhang *et al.* (2019) introduced low-carbon economic variables and developed a cold chain logistics path optimization model.

With the continued development of cold chain logistics, scholars have also evaluated and analyzed the efficiency of fresh food cold chain logistics for a particular region or company. Joshi *et al.* (2011) evaluated the efficiency of the company's cold chain logistics using Delphi, analytic hierarchy process (AHP) and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). Based on the DEA model and Malmquist index model, Zhong (2014) assessed the efficiency of agricultural logistics in 24 provinces of China from 2008 to 2011. Duman *et al.* (2017) measured the overall operational efficiency of the food industry through a combination of fuzzy AHP, DEA and TOPSIS methods. Yu *et al.* (2020) analyzed the cold chain logistics efficiency of agricultural products in Jilin Province, China from 2009 to 2018 based on the DEA model.

In short, the existing literature on fresh food cold chain logistics focuses mostly on technical improvements, management strategies and policy analysis, but the systematic assessment of cold chain logistics efficiency is more limited, especially the lack of analysis of efficiency differences and their causes.

2.2 Application of the DEA model

Charnes *et al.* (1978) proposed a DEA method to evaluate the efficiency of each decision-making unit (DMU) relative to the best-performing units within the same dataset by comparing their inputs and outputs. The basic DEA model Charnes *et al.* (1978) developed was named the CCR model after them. CCR model means that all DMUs operate under the condition of constant return to scale (CRS). Based on the CCR model, Banker *et al.* (1989) established the BCC model of variable return to scale (VRS).

In recent years, DEA has been widely used in efficiency measurement studies in logistics. The CCR and BCC models had been used to research the efficiency of agricultural logistics in Jiangsu (Yu *et al.*, 2019) and Jilin (Yu *et al.*, 2020) Provinces in China. Hamdan and Rogers (2008) presented a revised DEA model and constructed an index evaluation system to analyze the efficiency of 19 warehousing centers of a third-party logistics enterprise in the United States. Wu *et al.* (2019) extended the DEA model by breaking the homogeneity assumption of the traditional DEA model. The CCR-DEA and BCC-DEA models are radial models, emphasizing the same proportional increase or decrease of inputs and outputs. Slack variables derived from the radial model might lead to deviations in the measurement results from the actual situation. Accordingly, Tone (2001) proposed a slacks-based measure (SBM) model, a non-radial DEA model that can overcome the defect well. Ho *et al.* (2022) used the super-SBM model to assess the performance of logistics companies in Vietnam before and after strategic alliances, which provides a reference for logistics companies to choose partners.

The basic DEA and its improved models are single-stage DEA models. They consider only controllable inputs and outputs, thus ignoring the impact of environmental and other uncontrollable factors on efficiency. As a result, some researchers have examined the impact of uncontrollable factors on efficiency by including regression analysis as a second stage following DEA calculations. Rodrigues *et al.* (2018) used CCR, BCC and robust regression approach to identify the variables affecting the efficiency of third-party logistics (3PL) providers in refrigeration services. Zheng *et al.* (2020) integrated the SBM model and hierarchical regression to discuss how internal and external factors influence regional logistics efficiency. However, two-stage DEA models sometimes fail to adequately isolate the impacts of external factors and statistical noise, resulting in less accurate efficiency estimates. To address this limitation, Fried *et al.* (2002) proposed a three-stage DEA model based on BCC model and SFA (Aigner *et al.*, 1977). Based on the BCC model's initial calculations, SFA is employed in the second stage to distinguish the influence of external environmental elements from statistical noise. Following that, BCC is applied again to the modified data, yielding more precise efficiency estimates. Yan and Zhang (2011) used a three-stage DEA model to calculate the logistics efficiency in 31 provinces in China. Chen *et al.* (2021) measured the agricultural green total factor productivity by using a three-stage SBM-DEA model. Liang *et al.* (2022) used the three-stage super-SBM model and Malmquist index model to evaluate the logistics efficiency of 13 cities in Jiangsu Province. Scholars in the field of logistics have constructed their own DEA indicators for studying from different perspectives, such as geography and companies. Table 1 summarizes some of the indicator systems for DEA models in logistics.

Although DEA models are widely used in logistics efficiency evaluation, there are still fewer studies on the application of three-stage DEA models in the field of cold chain logistics, especially fresh cold chain logistics. Most of the existing studies using three-stage DEA models were based on CCR and BCC models, and fewer used more advanced DEA models such as SBM.

Therefore, by applying a three-stage SBM-DEA model to assess the efficiency of fresh food cold chain logistics in 30 provinces in China, this study enriches the research on model application and empirical analysis. This study revealed regional differences by comparatively analyzing the efficiency of different provinces and economic zones over the period 2013–2019. By analyzing the main factors affecting efficiency, the study provided appropriate recommendations.

3. Methodology

This study focused on efficiency as the relationship between inputs and outputs in the fresh food cold chain logistics industry. Traditional DEA models are not able to identify the effects of environmental factors and stochastic noise on efficiency. Two-stage DEA combined with regression analysis can separate the effects of uncontrollable factors from the efficiency results and adjust the efficiency results. The three-stage DEA model proposed by Fried *et al.* (2002) based on this, adjusts the inputs or outputs to make the measurements closer to reality. The first stage of the traditional three-stage DEA model uses the radial CCR or BBC model. This study used the non-radial SBM-DEA model (Tone, 2001) to identify slack variable values more accurately. SFA (Aigner *et al.*, 1977) and DEA are both commonly used methods for measuring efficiency. DEA is a non-parametric approach that assesses relative efficiency by constructing a production frontier surface. The efficiency measured by DEA is not affected by the unit of data selected. SFA is a parametric approach that requires a pre-determined form of the production function to estimate the parameters, which allows for the division of the error term into stochastic noise and managerial inefficiencies (Bogetoft and Otto, 2010). The three-stage DEA model combines the advantages of these two models. After obtaining the results from the SBM model, the outputs can be adjusted to remove environmental factors using the SFA model. The third stage utilizes the SBM model to evaluate the adjusted data to produce more accurate and fairer results.

3.1 SBM-DEA model

Assuming that there are N homogeneous DMUs to be evaluated, each DMU has M kinds of inputs and R kinds of outputs. For $DMU_k(k = 1, 2, \ldots, N)$, the input vector is $x_{mk} = (x_{1k}, x_{2k}, \ldots, x_{Mk})$ and the output vector is $y_{rk} = (y_{1k}, y_{2k}, \ldots, y_{Rk})$. The basic SBM model for k-th DMU with VRS is shown in Model (1).

Authors	Methods	Inputs	Outputs	Environmental variables	Sample
Rodrigues *et al.* (2018)	CCR, BCC, Robust regression	Number of employees, Total warehouse area, Number of total warehouses	Gross revenues, Number of clients	Transportation services, Inventory and warehousing services, Value-added services, Legislation-related service	45 3PL cold chain providers in Brazil (2008–2016)
Deng *et al.* (2020)	SBM, PCA, Tobit model	Highway mileage, Number of road trucks, Fixed asset investment, Number of legal entities, Average salary of employed persons	Logistics industry added value, Logistics industry carbon emissions	Economic development, Industrial structure, Government expenditure, Energy structure	30 provinces in China (2016)
Dixit *et al.* (2020)	CCR, BCC	Warehouse storage capacity, Temperature-controlled storage capacity, Number of skilled employees, Operational cost	Order fill rate, Number of generic drugs, Volume of drugs, Consumption points, Inventory turns ratio, Time efficiency	–	30 drug warehouses in India
Lu *et al.* (2020)	Three-stage DEA (BCC-SFA-BCC)	Net fixed assets, Employee salary, Main business cost, Environmental protection investment rate, Cold chain technology investment rate	Return on total assets, Operating revenue growth rate, Cold chain delivery on ton-timeline rate	The establishment years of the enterprise, Local GDP, Proportion of cold chain assets	29 listed logistics enterprises in China (2018)
Tian *et al.* (2020)	Factor analysis method, Super-efficiency SBM-DEA model with weighting preference	Total investment in fixed assets, Number of employees, Proportion of living expenditure in the transportation sector	Economic loss of traffic accidents, Proportion of employees in junior college and higher education, GDP of transportation, Average earnings of employees etc.	–	Sixteen years as the DMUs, Shaanxi province in China (2000–2015)

(*continued*)

Table 1.
Inputs, outputs and environmental variables of DEA in the related logistics field literature

Authors	Methods	Inputs	Outputs	Environmental variables	Sample
Yu *et al.* (2020)	CCR, BCC	Number of employees in the agricultural product logistics industry, Fixed assets investment amount of agricultural product logistics	The added value of agricultural product logistics	–	Ten years as the DMUs, Jilin province in China (2009–2018)
Zheng *et al.* (2020)	SBM, Hierarchical regression	Investment in fixed assets, Length of the logistics network, Postal outlets, Terminal energy consumption	Cargo volume, Gross product of the logistics industry, Carbon emissions	Regional population, Economic development level, Opening up level, Specialization degree of logistics industry, Government support, Government regulation	18 provinces in China along the Belt and Road Initiative (2007–2017)
Gan *et al.* (2022)	Three-stage DEA (BCC-SFA-BCC)	Fixed assets investment, Energy consumption, Number of employees	Total amount of post and telecommunication business, Added value of tertiary industry	GDP, R&D expenditure (Scientific research funds and the cost of scientific research)	11 cities in Jiangxi Province in China (2013–2019)
Jiang *et al.* (2022)	Cross-efficiency evaluation, secondary goal model	Number of logistics employees, Ownership of civil vehicles, Mileage of class highway	Urban GDP, Cargo turnover, CO_2 emissions from electricity	–	16 cities in the Anhui Province of China (2019)
Li *et al.* (2022)	Four-stage DEA (BCC-SFA-BCC-Tobit)	Total length of each production berth, Number of berths used for port operations	Annual inbound and outbound cargo volume, Annual inbound and outbound container volume	GDP of port hinterland cities, Fixed asset investment in tertiary industry, Total import and export volume of port hinterland cities, Highway network density, Number of buses (electric) in hinterland cities	20 coastal ports in China (2014–2018)

(continued)

Table 1.

Authors	Methods	Inputs	Outputs	Environmental variables	Sample
Liang *et al.* (2022)	Three-stage DEA (Super-SBM-SFA-Super-SBM, Malmquist)	Total mileage, Capital stock, Number of employees	Freight volume, Cargo turnover, GDP of the logistics industry, CO2 emission	Logistics industry density, Urbanization level, Logistics specialization level	13 cities in Jiangsu province in China (2010–2020)
Ran *et al.* (2022)	Three-stage DEA (BCC-SFA-BCC)	Fixed asset investment, Number of employees, Proportion of financial expenditure of logistics industry in local financial expenditure	Volume of freight transport, Rotation volume of freight transport, GDP of the logistics industry	Consumption level of regional residents, Total retail sales of social consumer goods, Regional per capita GDP	31 provinces in China (2009–2018)

Table 1.

Source(s): Table summarized by authors

$$Min\,\rho_k = \frac{1 - \frac{1}{M}\sum_{m=1}^{M} S^-_{mk} \Big/ x_{mk}}{1 + \frac{1}{R}\sum_{r=1}^{R} S^+_{rk} \Big/ y_{rk}}$$

$$\begin{aligned}
\text{s.t.} \ & \sum_{n=1}^{N} \lambda_n x_{mn} + S^-_{mk} = x_{mk}, m \in (1, 2, \ldots, M) \\
& \sum_{n=1}^{N} \lambda_n y_{rn} - S^+_{rk} = y_{rk}, r \in (1, 2, \ldots, R) \\
& \sum_{n=1}^{N} \lambda_n = 1 \\
& \lambda_n, S^-_{mk}, S^+_{rk} \geq 0 \\
& n = 1, 2, \ldots, N
\end{aligned} \tag{1}$$

DEA models can be categorized into input-oriented and output-oriented models (Tone, 2001; Cook *et al.*, 2014). Output-oriented models are more concerned with producing as much output as possible rather than cutting inputs (Dixit *et al.*, 2020). China's fresh food cold chain logistics is still rapidly developing. This study hoped to maximize the outputs with the available resources. Therefore, the output-oriented SBM model (Model (2)) based on Model (1) was chosen to identify which output indicators can be further improved. ρ^*_O is the efficiency value.

$$
\begin{aligned}
& Max\ \frac{1}{\rho_O^*} = 1 + \frac{1}{R}\sum_{r=1}^{R}\frac{S_{rk}^+}{y_{rk}} \\
& s.t.\ \sum_{n=1}^{N}\lambda_n x_{mn} + S_{mk}^- = x_{mk}, m \in (1,2,...,M) \\
& \sum_{n=1}^{N}\lambda_n y_{rn} - S_{rk}^+ = y_{rk}, r \in (1,2,...,R) \\
& \sum_{n=1}^{N}\lambda_n = 1 \\
& \lambda_n, S_{mk}^-, S_{rk}^+ \geq 0 \\
& n = 1,2,...,N
\end{aligned} \tag{2}
$$

In Model (1) and (2), $\lambda_n = (\lambda_1, \lambda_2, \ldots, \lambda_N)$ is the unknown non-negative weight vector used to construct the reference sets. The reference sets $\sum_{n=1}^{N}\lambda_n x_{mn}$ and $\sum_{n=1}^{N}\lambda_n y_{rn}$ constitutes the efficiency frontier of the DEA through linear combinations. S_{mk}^- and S_{rk}^+ are the slack variables of input x_{mk} and output y_{rk}, respectively. They indicate the gap between the inputs and outputs of DMUs and the production frontier (optimal combination). ρ_k and ρ_O^* is the efficiency value, between 0 and 1. If $\rho_O^* = 1$ and $S_{mk}^- = S_{rk}^+ = 0$, the DMU is efficient. The efficiency obtained from Model (2) is pure technical efficiency (PTE), which reflects how effectively the DMU is managed and operated at optimal size. Model (2) with the convexity constraint $\sum_{n=1}^{N}\lambda_n = 1$ removed is the output-oriented SBM model under the CRS condition and can obtain technical efficiency (TE). TE refers to the efficiency of actual output compared to the optimal frontier. Scale efficiency (SE) is the ratio of TE to PTE and reflects the efficiency of the current production scale compared to the optimal production scale (Dixit *et al.*, 2020).

3.2 The three-stage DEA model

3.2.1 The first stage: efficiency measurement of output-oriented SBM model. In the first stage, a preliminary analysis of the input and output data collected from the research subject is conducted by applying the output-oriented SBM-DEA model. This study can obtain TE, PT, SE and S_{rk}^+ using RStudio software.

3.2.2 The second stage: SFA regression analysis. The second stage focuses on slack variables of output indicators. The slack variables are influenced by environmental effects, managerial inefficiencies and statistical noise. SFA regression can decompose S_{rk}^+ of the first stage into the three effects mentioned above.

The following SFA regression function can be constructed.

$$S_{rk}^+ = f(Z_k;\beta) + v_{rk} + u_{rk}, r = 1,2,\ldots,R;\ k = 1,2,\ldots,N \tag{3}$$

$$f(Z_k;\beta) = \beta_0 + \beta_1 z_{1k} + \beta_2 z_{2k} + \ldots + \beta_P z_{Pk} \tag{4}$$

where S_{rk}^+ is the slack value of the r-th output indicator of the k-th DMU. $Z_k = (z_{1k}, z_{2k}, \ldots, z_{Pk})$ is the vector of P environmental variables for the k-th DMU. $\beta = (\beta_1, \beta_2, \ldots, \beta_P)$ is the coefficient of the environmental variable Z_k. β_0 is a constant term. $f(Z_k;\beta)$ is a regression function describing the effect of environmental variables on the slack values. $v_{rk} + u_{rk}$ is a mixed error term. v_{rk} indicates stochastic interference and $v_{rk} \sim N(0, \sigma_v^2)$. u_{rk} is a non-negative random variable that reflects managerial inefficiency and $u_{rk} \sim N^+(0, \sigma_u^2)$.

By maximum likelihood estimation, regression model (3) can estimate the parameters β, σ_v^2 and σ_u^2. If $\gamma = \frac{\sigma_u^2}{\sigma_u{}^2 + \sigma_v{}^2}$ is close to 1, management inefficiency is the main effect on the slack variable. According to the model of Jondrow *et al.* (1982), the expected value of the management inefficiency term can be calculated by equation (5). Then, equation (6) can calculate the expected value of statistical noise.

$$\widehat{E}(u_{rk}|\varepsilon_{rk}) = \frac{\sigma_u + \sigma_v}{\sigma}\left[\frac{\phi\left(\frac{\varepsilon_{rk}}{\sigma}\right)}{\Phi\left(\frac{\varepsilon_{rk}}{\sigma}\right)} + \frac{\varepsilon_{rk}\sigma_u}{\sigma_v\sigma}\right] \tag{5}$$

$$\widehat{E}(v_{rk}|\varepsilon_{rk}) = S_{rk}^{+} - Z_k\widehat{\beta} - \widehat{E}(u_{rk}|\varepsilon_{rk}) \tag{6}$$

where $\varepsilon_{rk} = v_{rk} + u_{rk}$, $\sigma^2 = \sigma_u{}^2 + \sigma_v{}^2$.The output variables of DMUs can be adjusted according to the regression results by using equation (7).

$$y_{rk}^{*} = y_{rk} + [\max(f(Z_k;\widehat{\beta})) - f(Z_k;\widehat{\beta})] + [\max(\widehat{v_{rk}}) - \widehat{v_{rk}}], r = 1, 2, \ldots, R;\ k = 1, 2, \ldots, N \tag{7}$$

y_{rk}^{*} is the adjusted output. y_{rk} is the original output. $[\max(f(Z_k;\widehat{\beta})) - f(Z_k;\widehat{\beta})]$ can adjust all DMUs to the same environment. $[\max(\widehat{v_{rk}}) - \widehat{v_{rk}}]$ represents elimination of the effects of statistical noise.

3.2.3 The third stage: DEA efficiency analysis of adjusted input-output variables. The third stage repeats the first stage. This stage replaces the original output y_{rk} with the adjusted output y_{rk}^{*}. The resulting efficiency values have been removed from the effects of environmental and random factors. The results provide a more objective and effective reflection of the development level of fresh food cold chain logistics in China.

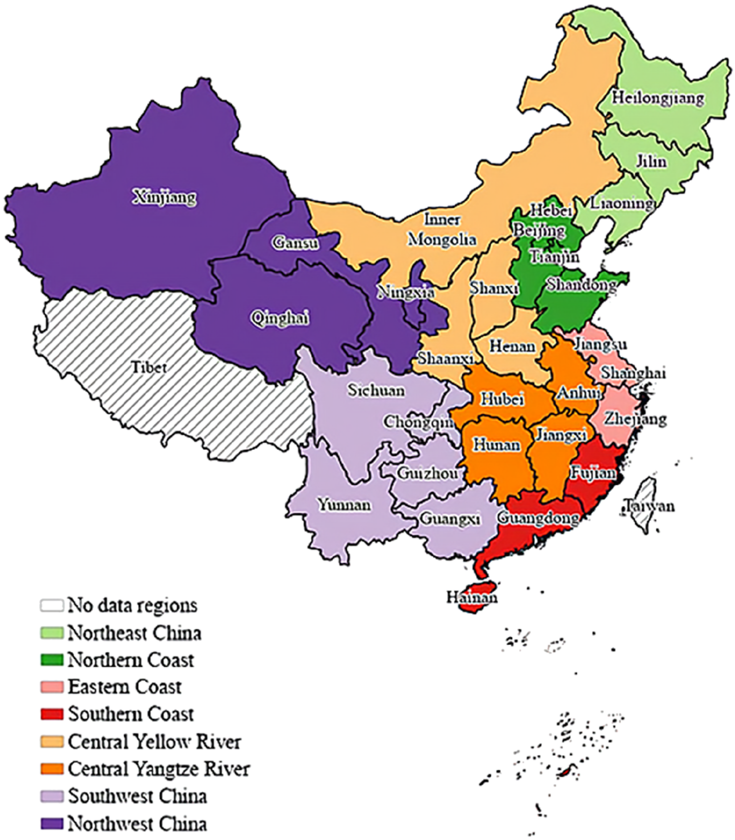
4. DMUs, indicators and data

4.1 DMUs and regional division

Based on a report issued by the Development Research Centre of the State Council, this study divided the 30 provinces (as DMUs) into eight economic regions. The division of economic zones is based on characteristics such as geography, distribution of natural resources and industrial structure. The detailed provinces of eight regions are shown in Figure 1 and Table 2.

4.2 Selection of indicators

Based on the principle that the number of DMUs of the DEA model is not less than twice the sum of the number of input and output indicators (Avkiran, 2001; Chen and Jia, 2017; Zheng *et al.*, 2020), this study selected 3 input indicators and 2 output indicators. For DEA models, it is important for selecting indicators to consider the validity, importance, correlation, comparability and operability of the indicators (Luo *et al.*, 2012; Cook *et al.*, 2014; Liang *et al.*, 2022). This means that the indicators used should sufficiently reflect the industry's operations and features while also allowing for vertical and horizontal comparisons among



Source(s): Authors' own work

Figure 1. The detailed provinces of eight regions

Regional division	Provinces in the region
Northeast China	Liaoning, Jilin, Heilongjiang
Northern Coast	Beijing, Tianjin, Hebei, Shandong
Eastern Coast	Shanghai, Jiangsu, Zhejiang
Southern Coast	Fujian, Guangdong, Hainan
Central Yellow River	Shanxi, Inner Mongolia, Henan, Shaanxi
Central Yangtze River	Anhui, Jiangxi, Hubei, Hunan
Southwest China	Guangxi, Chongqing, Sichuan, Guizhou, Yunnan
Northwest China	Gansu, Qinghai, Ningxia, Xinjiang

Source(s): Authors' own work

Table 2. The detailed provinces of eight regions

DMUs. Indicator data should be straightforward to gather and come from reliable sources. Table 3 shows the indicators considered for the study based on these concepts and related literature.

Input factors include financial, human and material resources in the process of cold chain logistics activities. According to other researchers' studies, fixed asset investment and the

Type	Indicator	Definition	Unit	Literature sources
Input	Fixed asset investment	Total amount of fresh food cold chain logistics fixed asset investment	100 million yuan	Deng *et al.* (2020), Lu *et al.* (2020), Tian *et al.* (2020), Yu *et al.* (2020), Zheng *et al.* (2020), Gan *et al.* (2022), Liang *et al.* (2022), Ran *et al.* (2022)
	Employees	Total number of employees related to logistics	10 thousand people	Rodrigues *et al.* (2018), Dixit *et al.* (2020), Jiang *et al.* (2022), Tian *et al.* (2020), Yu *et al.* (2020), Gan *et al.* (2022), Liang *et al.* (2022), Ran *et al.* (2022)
	Cold storage	Total capacity of cold storage	10 thousand tons	Dixit *et al.* (2020)
Output	Freight volume	Total freight volume of fresh food cold chain logistics	10 thousand tons	Jiang *et al.* (2022), Zheng *et al.* (2020), Liang *et al.* (2022), Ran *et al.* (2022)
	Industry value added	Total added value of fresh food cold chain logistics industry	100 million yuan	Deng *et al.* (2020), Yu *et al.* (2020), Gan *et al.* (2022)
Environmental Variables	Regional development level	The total regional GDP	100 million yuan	Lu *et al.* (2020), Gan *et al.* (2022), Li *et al.* (2022), Ran *et al.* (2022)
	Regional population size	Year-end population of the region	10 thousand people	Zheng *et al.* (2020), Liang *et al.* (2022)
	Government support	The ratio of local government's financial expenditures on transportation to general budget expenditures	–	Zheng *et al.* (2020), Gan *et al.* (2022)

Source(s): Authors' own work

Table 3.
Fresh food cold chain logistics evaluation indicator system

number of employees are frequently considered inputs. Fixed asset investment is an important metric for evaluating efficiency in the fresh food cold chain logistics. The number of employees can indicate the amount of labor input in the industry. Cold storage is essential for preserving fresh foods. Cold storage capacity can reflect the ability of cold chain logistics operation.

Output factors are the tangible and intangible outputs obtained from the participation of input factors in productive activities. In the logistics industry, tangible outputs include freight volume and cargo turnover. Intangible outputs are economic outputs, which can be reflected by gross industrial output, operating income and industry value added. Due to data operability, freight volume and industry value added were selected as output indicators for this study.

To ensure the scientific validity of the measurement results of fresh cold chain logistics efficiency, this study applied RStudio software to make Pearson correlation tests on input and output indicators (Table 4). The results show that the Pearson correlation coefficients of the input and output indicators selected in this study are positive and significant at the 1%

level. This indicates that there are positive correlations between the indicators. The selected indicators are reasonable.

Environment variables can impact the efficiency of DMUs, and they are not subject to subjective control by DMUs themselves. GDP can reflect the level of economic development and people's living standards in a region. It has an impact on the capital environment of fresh food cold chain logistics because of the large regional differences. Population distribution is highly correlated with freight activity (Kang, 2020). Logistics companies consider more populated areas when making location decisions (Nguyen and Sano, 2010) because areas with large population sizes can provide relatively more labor force. The level of government support would affect the local incentive to develop cold chain logistics, such as financial subsidies provided by different local governments, policy support for infrastructure and so on. The government support selected for this study uses the ratio of local government expenditures on transportation to general budget expenditures.

4.3 Data sources and processing

This study is based on a research sample of 30 provincial-level administrative regions (or municipalities directly under the central government), excluding Hong Kong, Macao, Taiwan and Tibet. The study period is from 2013 to 2019. The relevant raw data were obtained from the 2014–2020 "China Statistical Yearbook", "China Rural Statistical Yearbook", "China Logistics Statistical Yearbook", "China Cold Chain Logistics Development Report" and the official website of the National Bureau of Statistics. Due to COVID-19 in 2020, cold storage capacity data from the same data source is not available after 2019. Referring to the scope of the literature in Table 1, the use of multi-period data can identify the changes in DMUs in terms of efficiency, which helps to find the factors affecting the changes. This still has generalized empirical value for the development evaluation of the fresh food cold chain logistics industry.

Since there is no complete statistical data specifically for the logistics industry in China, the data of some indicators are not directly available. According to the China Logistics Yearbook, the transportation, storage and postal industries contribute more than 80% of the logistics industry's added value. These industries can reflect the overall growth of the logistics sector (Deng *et al.*, 2020; Zheng *et al.*, 2020; Liang *et al.*, 2022). Hence, this study is also based on these industries for data collection. Using 2010 as the baseline, this study converted industry value added, regional GDP and fixed asset investment amounts to constant prices using GDP and fixed asset investment deflators for each province, to avoid the interference of price changes on the analysis results. Table 5 shows the descriptive statistics of input and output indicators.

Indicators	Fixed asset investment	Employees	Cold storage	Freight volume	Industry value-added
Fixed asset investment	1.0000				
Employees	0.4180***	1.0000			
Cold storage	0.4485***	0.5876***	1.0000		
Freight volume	0.8362***	0.4492***	0.5874***	1.0000	
Industry value added	0.7945***	0.4623***	0.6465***	0.9314***	1.0000

Note(s): ***means significance at 1%
Source(s): Authors' own work

Table 4. Pearson coefficient of the input and output indicators

5. Results

5.1 Analysis of the first stage results

Substituting the processed data into the output-oriented SBM model, this study obtained the efficiency results of fresh food cold chain logistics from 2013 to 2019 for 30 provinces in China. Figures 2–4 show TE, PTE and SE for different provinces in different years, respectively. Figure 5 illustrates the average TE of the eight regions for each year.

The overall efficiency of fresh food cold chain logistics in China is low, averaging 0.545 in seven years. The TE, PTE and SE values of Anhui all reach 1 during the period from 2013 to 2019. Anhui's cold chain logistics resources were effectively utilized. The TE of Hebei and Henan during this seven-year period is very close to 1. It shows that the allocation and utilization of resources in fresh food cold chain logistics in the above three provinces are reasonable and effective. Hebei and Henan provinces are both large agricultural provinces. Due to the Beijing–Tianjin–Hebei logistics network, Hebei Province undertakes the task of delivering fresh food to Beijing and Tianjin. Henan Province is the largest frozen food processing base in China, as well as a hub for transportation in China. It has advantages in cold chain logistics development. TE of the 22 provinces are less than 1 in each of the seven years. Between 2013 and 2019, most of the provinces' SE values are concentrated between 0.8

Table 5. Descriptive statistics of indicators (2013–2019)

Indicators	Min	Max	Mean	Std. dev.
Fixed asset investment	1.83	62.83	21.89	15.75
Employees	3.67	86.41	28.01	17.19
Cold storage	6.57	934.73	144.73	129.74
Freight volume	209.50	13369.00	3792.70	3063.12
Industry value added	1.25	149.77	28.85	31.25
Regional development level	158.6	9078.8	2329.9	1851.73
Regional population size	571	12,489	4,617	2854.92
Government support	0.0228	0.1612	0.0649	0.0233

Source(s): Authors' own work

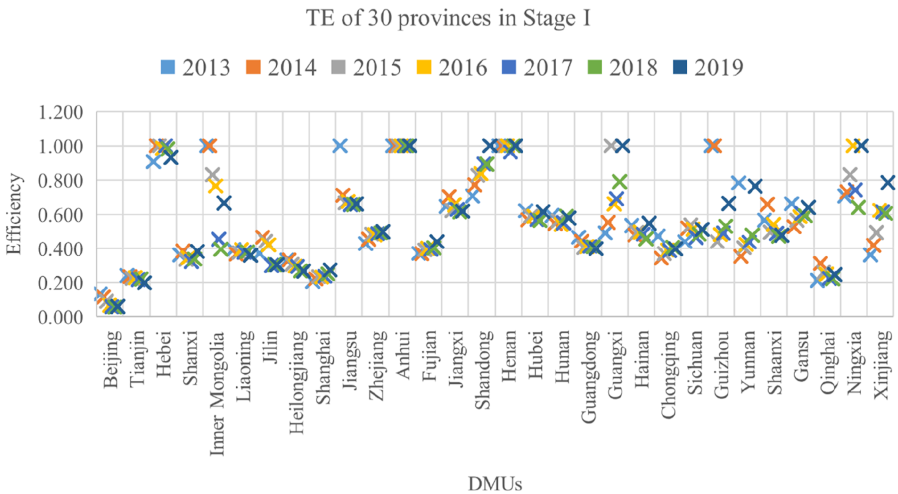


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Figure 2. Technical efficiency of fresh food cold chain logistics in China in Stage I

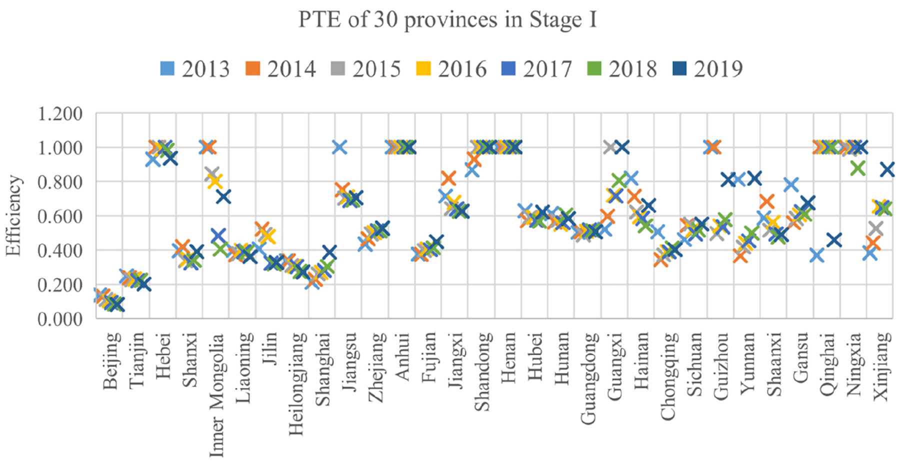

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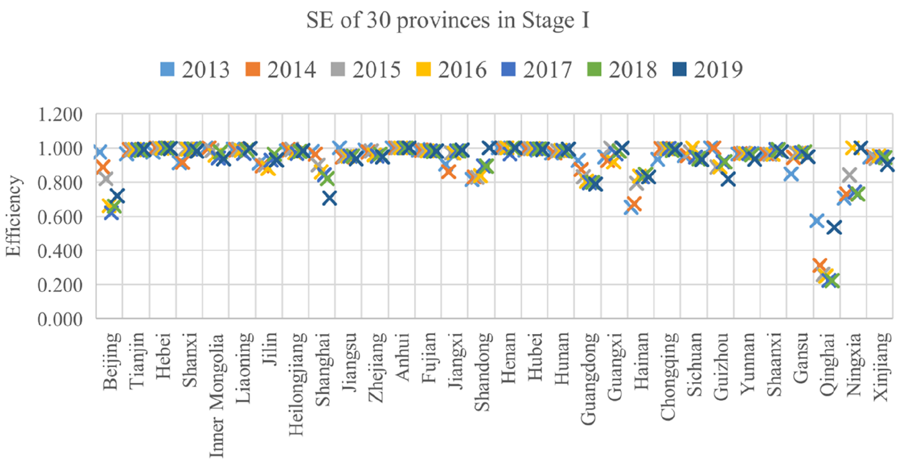
Figure 3. Pure technical efficiency of fresh food cold chain logistics in China in Stage I



Source(s): Authors' own work

Figure 4. Scale efficiency of fresh food cold chain logistics in China in Stage I

and 1, but with low PTE values. This indicates their TE is mainly influenced by PTE, such as Zhejiang and Shanghai. These provinces need to further improve their cold chain logistics technology to match the existing scale.

There are relatively large differences in efficiency between regions. According to Figure 5, the trends in TE in the coastal zone (Northern Coast, Eastern Coast and Southern Coast) and Central Yangtze River are relatively flat between 2013 and 2019. The TE fluctuates more in the Central Yellow River and Northwest China within 7 years. The overall TE of Northeast China is consistently below 0.4.

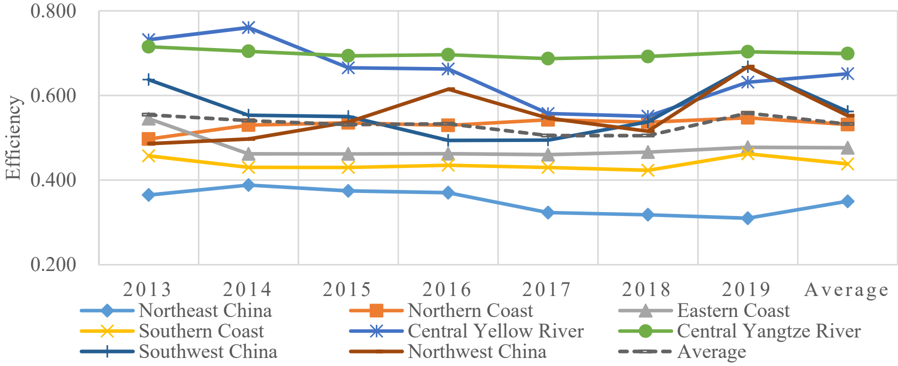


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Figure 5.
Trends in average TE for the 8 regions in Stage I

Since the results of the first stage cannot determine whether efficiency is overestimated, a second stage is needed to analyze external factors.

5.2 Analysis of the second stage results

From the SFA results (Table 6), LR values all passed 1% significance test, which shows the SFA regression model used in this study is reasonable. γ is close to 1 and passes the 1% significance test, which indicates management inefficiency has a larger effect on the slack variables than statistical noise.

Regional GDP (Z1) positively correlates with slack variables in freight volume and industry value added, both significant at the 1% level. As regional GDP rises, freight volume

Slacks variables	Parameters	Coefficient	Standard error	T-ratio
Freight volume	coefficient	213.5096	210.2629	1.0154
	Z1	0.2679	0.1008	2.6594***
	Z2	−0.1689	0.0647	−2.6122***
	Z3	−1678.2592	377.4698	−4.4461***
	σ^2	5165466.7	1.2838	4023435.1***
	γ	0.9340	0.0069	135.24717***
	Log likelihood function		−1689.5412	
	LR test of the one-sided error		277.9083***	
Industry value added	coefficient	−3.2509	3.8703	−0.8400
	Z1	0.0036	0.0011	3.3528***
	Z2	−0.0013	0.0006	−2.3330**
	Z3	−1.0868	32.8537	−0.0331
	σ^2	704.88	184.81	3.8141***
	γ	0.94	0.02	57.7629***
	Log likelihood function		−739.8856	
	LR test of the one-sided error		286.5589***	

Note(s): *, **, *** mean significance at 10%, 5% or 1%, respectively
Source(s): Authors' own work

Table 6.
SFA regression results in Stage II

and industry value added decrease. This indicates that high GDP provinces have not been able to efficiently convert the available inputs into corresponding outputs. High GDP provinces should focus on the effective resource allocation and management, optimize the operation mechanism of cold chain logistics and strengthen logistics informationization.

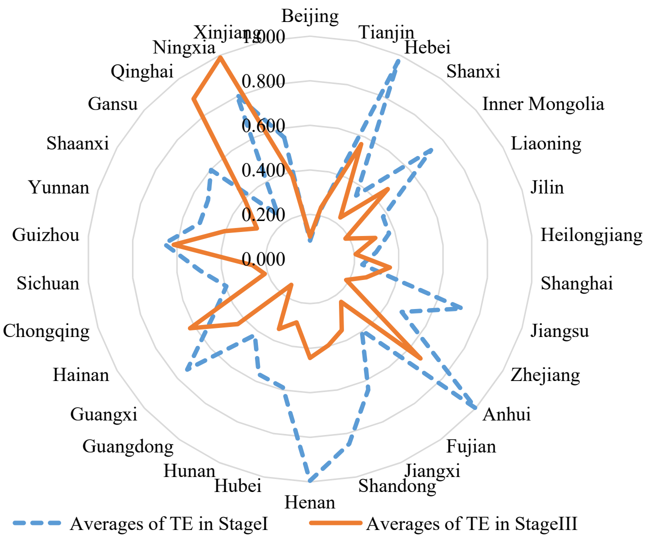
Regional population size (Z2) shows a negative correlation with slack variables in freight volume and industry value added, significant at 1% and 5%, respectively. This is since areas with larger populations have greater market demand, which drives the efficiency of cold chain logistics. Provinces with small populations can expand their services through interregional cooperation and resource sharing.

Government support (Z3) exhibits a significant and negative association with slack variables in freight volume, indicating that increased government investment reduces freight volume insufficiency and enhances fresh food cold chain logistics efficiency. However, the regression coefficient for the slack variable of industry value added is non-significant, suggesting that government support has no theoretical impact on the productive efficiency of industry value added. The government should increase support for cold chain logistics and develop tailored subsidy policies.

5.3 Analysis of the third stage results

The adjusted outputs and the original inputs were used to measure the actual efficiency using the output-oriented SBM model. After excluding external environmental variables and random disturbances, the three efficiency values varied significantly. The development level of fresh food cold chain logistics in most provinces has not reached the level it has shown in the first stage. The economic level, regional population size and government support overall have a positive impact on the development of the industry.

The national average TE and average SE from 2013 to 2019 are 0.382 and 0.551, which are 29.9% and 40.0% lower than the first stage results, respectively. The national average PTE is 0.668, an improvement of 16.7%. This indicates that PTE is underestimated. The overestimated SE leads to a decrease in TE. According to Figure 6, the average TEs decrease



Source(s): Authors' own work

Figure 6.
The radar chart of 30 provinces' average TE changes, 2013–2019

in 24 provinces, such as Hebei, Inner Mongolia, Zhejiang and Henan. Environmental factors provide a good environment for evaluation in these provinces. These provinces need to strengthen their investment in cold chain logistics infrastructure, with the introduction of advanced technologies, such as the Internet of Things (IoT) and big data analysis (Badia-Melis *et al.*, 2018; Tsang *et al.*, 2018).

Combining Figures 7 and 8, Northwest China has a substantially higher average TE than other regions from 2013 to 2019. This region includes the livestock-rich provinces of Qinghai and Ningxia. The average TE and trends in the middle reaches of the Yangtze River, the southwest region and the southern coastal region are relatively close to the national general average. The mild climate in these regions is ideal for growing vegetables and fruits. They are the main production areas of fresh food in China. To preserve and transport fresh food products, the governments of these regions have paid more attention to the development of cold chain logistics and trained the relevant technical staff. The Central Yellow River region has a low average TE value. Its average PTE value is much higher than the average SE value. This suggests that the region should adjust the scale of production by controlling the industry's production elements, such as labor force and the level of management. The eastern coast, located in the Yangtze River Delta region, is one of China's most economically vibrant areas. Its average technical efficiency has fluctuated somewhat smoothly but remains notably lower than the national average. This aligns with SFA regression results showing a negative impact of regional economic development. The lower efficiency may stem from blind investment and expansion in high GDP regions, neglecting input resource rationality.

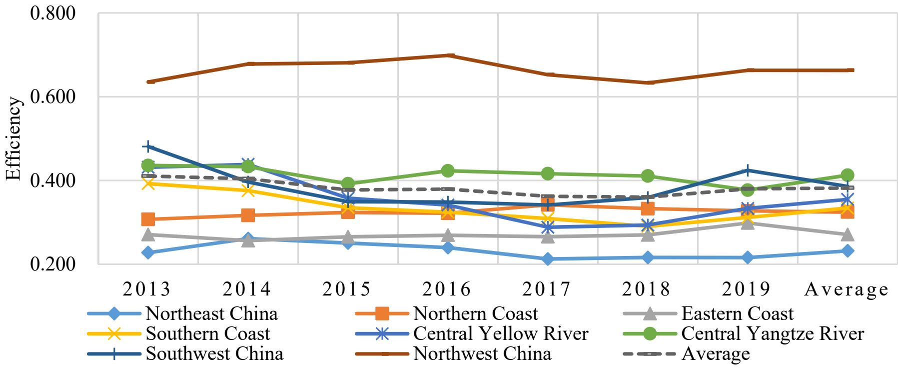


Figure 7.
Trends in average TE for the 8 regions in Stage III

Source(s): Authors' own work

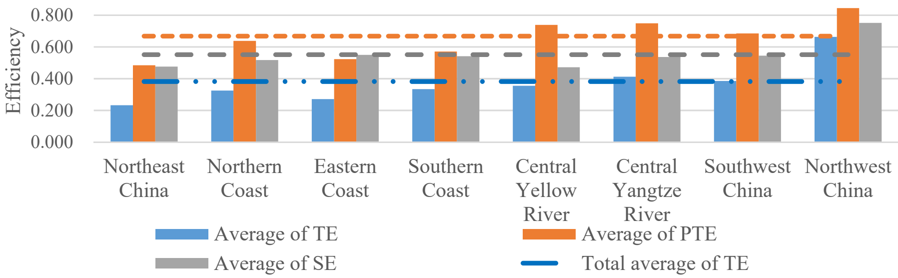


Figure 8.
Averages efficiencies for the 8 regions in Stage III

Source(s): Authors' own work

These regions should prioritize adjusting management practices and infrastructure alongside expanding cold chain logistics to ensure operational scale aligns with management and technical capabilities. All regions should strengthen cooperation and share advanced management experience and technology in cold chain logistics to improve efficiency.

6. Conclusions

China's fresh food cold chain logistics is developing rapidly, but still faces inefficiency problems such as wasted resources. This study adopted the analysis method of three-stage DEA model and constructed the efficiency evaluation indicator system based on the previous literature. This study assessed the actual efficiency of fresh food cold chain logistics in 30 provinces in China from 2013 to 2019 and analyzed the impact of the external environment on efficiency. Based on the results of the analysis, this study proposed appropriate recommendations to improve the efficiency of fresh food cold chain logistics.

The differences in fresh food cold chain logistics efficiency between the 30 provinces of the country measured in the first stage and the third stage over seven years are obvious. The adjusted technical efficiency is lower than that before the adjustment. This indicates that the efficiency of fresh food cold chain logistics is affected by external environmental factors and random interference. First, regional GDP is positively correlated with the slack variables of the two output indicators. High GDP provinces are not able to effectively transform available inputs into corresponding outputs and lead to the waste of resources. Blindly increasing investment and expanding the scale of the industry has resulted in the speed of technological level upgrading failing to keep up with the speed of scale expansion. Second, the regional population size is negatively correlated with the slack variables of the two output indicators. This suggests that provinces with large populations could further improve the quality of cold chain logistics services to meet wider market demand. Third, government support has a negative correlation with slack variable of freight volume and no significant correlation with slack variable of industry value added. Governments can promote the development of fresh food cold chain logistics by formulating targeted policies and increasing investment. For example, they can encourage enterprises to optimize management, tax incentives and subsidies (Gan *et al.*, 2022).

At the national level, the actual TE of China's fresh food cold chain logistics is low, with an average value of 0.382. The main reason for the low TE value is the low SE value. Therefore, while improving the level of technology, it is more important to focus on adjusting the scale of the industry and rationally allocating input resources to increase the scale efficiency.

The regional differences in the efficiency of fresh food cold chain logistics in China are obvious. Northwest China had the highest average technical efficiency, followed by the Central Yangtze River. The average technical efficiency values in the coastal region were lower compared to expectations. The average technical efficiency values in Northeast China were the lowest. Provinces in Northeast China should pay attention to increasing infrastructure development and technology introduction to improve output capacity. Both intra- and inter-regional cooperation should be pursued to share logistics resources and technologies to improve overall efficiency (Deng *et al.*, 2020).

The efficiency of fresh food cold chain logistics is not consistent with the level of regional economic development. The regions with good levels of economic development such as the northern coast and the eastern coast, their average technical efficiency values are much lower than those of Northwest China and the Central Yangtze River. Regions with good economic development have not effectively utilized existing resources and facilities. There is a need to optimize the layout of the cold chain logistics network and to improve transport efficiency (Ran *et al.*, 2022).

Based on the analysis of the efficiency of China's regional fresh food cold chain logistics from 2013 to 2019, this study provides valuable insights for other developing countries with significant agricultural sectors. By calculating the actual cold chain logistics efficiency in each region and identifying the factors affecting the efficiency, it is possible to have a clear picture of the development of the industry within the country. As the worldwide focus on cold chain logistics grows in response to COVID-19, many countries are rapidly extending their cold chain networks. However, this expansion should be planned strategically. Developing countries must carefully coordinate infrastructure development with available technology, assure skilled professional training and retention, and integrate new information technologies to maximize efficiency (Badia-Melis *et al.*, 2018; Tsang *et al.*, 2018; Jo *et al.*, 2022). Rapid growth, without a balanced and well-planned approach, can lead to inefficiencies, limiting cold chain logistics' ability to support agricultural development and food security.

This study contributes to the application of the DEA model in cold chain logistics by using the three-stage DEA model, which allows for a more precise evaluation of efficiency. The model separates environmental influences from stochastic noise, giving a more accurate representation of regional efficiency. This contribution is especially important for countries with complicated regional differences, thus the findings apply not only to China but also to other emerging countries confronting similar issues. The findings underscore the need for strategic planning in logistics infrastructure, particularly in the context of developing agricultural sectors.

Nevertheless, there are certain limits, particularly in the data collection. The cold storage capacity indicator, which is critical to this analysis, is difficult to obtain from a consistent and reliable source after 2019, hence this study concentrates on the pre-COVID-19 timeframe. As data availability in the cold chain logistics industry improves, future research can investigate larger datasets to analyze the influence of COVID-19 on cold chain logistics. In addition, although this paper constructs a comprehensive evaluation indicators system, it does not cover all aspects of fresh food cold chain logistics, such as food loss, refrigerated trucks and so on. The establishment of a more industry-specific indicator system is an aspect that needs to be studied in the future.

References

Abu Hassan, M.F., Ngah, A.H. and Ab Talib, M.S. (2021), "The state of cold logistics supply chain in a developing Asian country - a preliminary insights", *Operations and Supply Chain Management: An International Journal*, Vol. 14 No. 4, pp. 467-475, doi: 10.31387/oscm0470317.

Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977), "Formulation and estimation of stochastic Frontier production function models", *Journal of Econometrics*, Vol. 6 No. 1, pp. 21-37, doi: 10.1016/0304-4076(77)90052-5.

Amorim, P. and Almada-Lobo, B. (2014), "The impact of food perishability issues in the vehicle routing problem", *Computers and Industrial Engineering*, Vol. 67, pp. 223-233, doi: 10.1016/j.cie.2013.11.006.

Avkiran, N.K. (2001), "Investigating technical and scale efficiencies of Australian Universities through data envelopment analysis", *Socio-Economic Planning Sciences*, Vol. 35 No. 1, pp. 57-80, doi: 10.1016/s0038-0121(00)00010-0.

Badia-Melis, R., Mc Carthy, U., Ruiz-Garcia, L., Garcia-Hierro, J. and Robla Villalba, J.I. (2018), "New trends in cold chain monitoring applications - a review", *Food Control*, Vol. 86, pp. 170-182, doi: 10.1016/j.foodcont.2017.11.022.

Banker, R., Charnes, A., Cooper, W.W., Swarts, J. and Thomas, D.A. (1989), "AN introduction to data envelopment analysis with some OF its models and their uses", *Research in Governmental and Nonprofit Accounting*, Vol. 5 No. 1, pp. 125-163.

Bogetoft, P. and Otto, L. (2010), *Benchmarking with DEA, SFA, and R*, Vol. 157, Springer Science & Business Media.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978), "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444, doi: 10.1016/0377-2217(78)90138-8.

Chen, L. and Jia, G. (2017), "Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach", *Journal of Cleaner Production*, Vol. 142 No. Part 2, pp. 846-853, doi: 10.1016/j.jclepro.2016.01.045.

Chen, Y., Miao, J. and Zhu, Z. (2021), "Measuring green total factor productivity of China's agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO2 emissions", *Journal of Cleaner Production*, Vol. 318, 128543, doi: 10.1016/j.jclepro.2021.128543.

Cook, W.D., Tone, K. and Zhu, J. (2014), "Data envelopment analysis: prior to choosing a model", *Omega*, Vol. 44, pp. 1-4, doi: 10.1016/j.omega.2013.09.004.

Deng, F., Xu, L., Fang, Y., Gong, Q. and Li, Z. (2020), "PCA-DEA-tobit regression assessment with carbon emission constraints of China's logistics industry", *Journal of Cleaner Production*, Vol. 271, 122548, doi: 10.1016/j.jclepro.2020.122548.

Dixit, A., Routroy, S. and Dubey, S.K. (2020), "Measuring performance of government-supported drug warehouses using DEA to improve quality of drug distribution", *Journal of Advances in Management Research*, Vol. 17 No. 4, pp. 567-581, doi: 10.1108/jamr-12-2019-0227.

Dong, Y., Xu, M. and Miller, S.A. (2020), "Overview of cold chain development in China and methods of studying its environmental impacts", *Environmental Research Communications*, Vol. 2 No. 12, 122002, doi: 10.1088/2515-7620/abd622.

Duman, G.M., Tozanli, O., Kongar, E. and Gupta, S.M. (2017), "A holistic approach for performance evaluation using quantitative and qualitative data: a food industry case study", *Expert Systems with Applications*, Vol. 81, pp. 410-422, doi: 10.1016/j.eswa.2017.03.070.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S. and Yaisawarng, S. (2002), "Accounting for environmental effects and statistical noise in data envelopment analysis", *Journal of Productivity Analysis*, Vol. 17 Nos 1/2, pp. 157-174, doi: 10.1023/a:1013548723393.

Gan, W., Yao, W. and Huang, S. (2022), "Evaluation of green logistics efficiency in Jiangxi Province based on three-stage DEA from the perspective of high-quality development", *Sustainability*, Vol. 14 No. 2, p. 797, doi: 10.3390/su14020797.

Hamdan, A. and Rogers, K.J.J. (2008), "Evaluating the efficiency of 3PL logistics operations", *International Journal of Production Economics*, Vol. 113 No. 1, pp. 235-244, doi: 10.1016/j.ijpe.2007.05.019.

Han, J.-W., Zuo, M., Zhu, W.-Y., Zuo, J.-H., Lü, E.-L. and Yang, X.-T. (2021), "A comprehensive review of cold chain logistics for fresh agricultural products: current status, challenges, and future trends", *Trends in Food Science and Technology*, Vol. 109, pp. 536-551, doi: 10.1016/j.tifs.2021.01.066.

He, M., Yang, M., Wu, X., Pu, J. and Izui, K. (2024), "Evaluating and analyzing the efficiency and influencing factors of cold chain logistics in China's major urban agglomerations under carbon constraints", *Sustainability, Multidisciplinary Digital Publishing Institute*, Vol. 16 No. 5, p. 1997, doi: 10.3390/su16051997.

Ho, N.-N.-Y., Nguyen, P.M., Luu, T.-M.-N. and Tran, T.-T.-A. (2022), "Selecting partners in strategic alliances: an application of the SBM DEA model in the Vietnamese logistics industry", *Logistics*, Vol. 6 No. 3, p. 64, doi: 10.3390/logistics6030064.

Jiang, W., Liu, S. and Li, S. (2022), "An extended cross-efficiency evaluation method based on information entropy with an application to the urban logistics industry", *Journal of Modelling in Management*, Vol. 18 No. 2, pp. 578-601, doi: 10.1108/jm2-11-2021-0259.

Jo, J., Yi, S. and Lee, E. (2022), "Including the reefer chain into genuine beef cold chain architecture based on blockchain technology", *Journal of Cleaner Production*, Vol. 363, 132646, doi: 10.1016/j.jclepro.2022.132646.

Jondrow, J., Knox Lovell, C.A., Materov, I.S. and Schmidt, P. (1982), "On the estimation of technical inefficiency in the stochastic Frontier production function model", *Journal of Econometrics*, Vol. 19 Nos 2-3, pp. 233-238, doi: 10.1016/0304-4076(82)90004-5.

Joshi, R., Banwet, D.K. and Shankar, R. (2011), "A Delphi-AHP-TOPSIS based benchmarking framework for performance improvement of a cold chain", *Expert Systems with Applications*, Vol. 38 No. 8, pp. 10170-10182, doi: 10.1016/j.eswa.2011.02.072.

Kang, S. (2020), "Relative logistics sprawl: measuring changes in the relative distribution from warehouses to logistics businesses and the general population", *Journal of Transport Geography*, Vol. 83, 102636, doi: 10.1016/j.jtrangeo.2020.102636.

Kumar, A. and Agrawal, S. (2023), "Challenges and opportunities for agri-fresh food supply chain management in India", *Computers and Electronics in Agriculture*, Vol. 212, 108161, doi: 10.1016/j.compag.2023.108161.

Kuo, J.-C. and Chen, M.-C. (2010), "Developing an advanced multi-temperature joint distribution system for the food cold chain", *Food Control*, Vol. 21 No. 4, pp. 559-566, doi: 10.1016/j.foodcont.2009.08.007.

Li, H., Jiang, L., Liu, J. and Su, D. (2022), "Research on the evaluation of logistics efficiency in Chinese coastal ports based on the four-stage DEA model", *Journal of Marine Science and Engineering*, Vol. 10 No. 8, p. 1147, doi: 10.3390/jmse10081147.

Liang, Z., Chiu, Y., Guo, Q. and Liang, Z. (2022), "Low-carbon logistics efficiency: analysis on the statistical data of the logistics industry of 13 cities in Jiangsu Province, China", *Research in Transportation Business and Management*, Vol. 43, 100740, doi: 10.1016/j.rtbm.2021.100740.

Lu, Q., Chung, G.-Y. and Kim, H. (2020), "Analysis on logistics efficiency of China's agricultural products cold chain from the green perspective", *The International Journal of Advanced Culture Technology*, Vol. 8 No. 2, pp. 192-203, doi: 10.17703/ijact.2020.8.2.192.

Luo, Y., Bi, G. and Liang, L. (2012), "Input/output indicator selection for DEA efficiency evaluation: an empirical study of Chinese commercial banks", *Expert Systems with Applications*, Vol. 39 No. 1, pp. 1118-1123, doi: 10.1016/j.eswa.2011.07.111.

Nguyen, Y.C. and Sano, K. (2010), "Location choice model for logistic firms with consideration of spatial effects", *Transportation Research Record*, Vol. 2168 No. 1, pp. 17-23, doi: 10.3141/2168-03.

Ortiz-Gonzalo, D., Ørtenblad, S.B., Larsen, M.N., Suebpongsang, P. and Bruun, T.B. (2021), "Food loss and waste and the modernization of vegetable value chains in Thailand", *Resources, Conservation and Recycling*, Vol. 174, 105714, doi: 10.1016/j.resconrec.2021.105714.

Ran, W., Liu, R. and Liu, S. (2022), "Area differences in regional logistics efficiency and the law governing its temporal and spatial evolution", *Journal of Advanced Transportation*, Vol. 2022, pp. 1-14, doi: 10.1155/2022/3596524.

Raut, R.D., Gardas, B.B., Narwane, V.S. and Narkhede, B.E. (2019), "Improvement in the food losses in fruits and vegetable supply chain - a perspective of cold third-party logistics approach", *Operations Research Perspectives*, Vol. 6, 100117, doi: 10.1016/j.orp.2019.100117.

Ren, Q.-S., Fang, K., Yang, X.-T. and Han, J.-W. (2022), "Ensuring the quality of meat in cold chain logistics: a comprehensive review", *Trends in Food Science and Technology*, Vol. 119, pp. 133-151, doi: 10.1016/j.tifs.2021.12.006.

Rodrigues, A.C., Martins, R.S., Wanke, P.F. and Siegler, J. (2018), "Efficiency of specialized 3PL providers in an emerging economy", *International Journal of Production Economics*, Vol. 205, pp. 163-178, doi: 10.1016/j.ijpe.2018.09.012.

Solow, R.M. (1957), "Technical change and the aggregate production function", *The Review of Economics and Statistics*, Vol. 39 No. 3, p. 312, doi: 10.2307/1926047.

Tian, N., Tang, S., Che, A. and Wu, P. (2020), "Measuring regional transport sustainability using super-efficiency SBM-DEA with weighting preference", *Journal of Cleaner Production*, Vol. 242, 118474, doi: 10.1016/j.jclepro.2019.118474.

Tone, K. (2001), “A slacks-based measure of efficiency in data envelopment analysis”, *European Journal of Operational Research*, Vol. 130 No. 3, pp. 498-509, doi: 10.1016/s0377-2217(99)00407-5.

Trienekens, J.H., Wognum, P.M., Beulens, A.J.M. and van der Vorst, J.G.A.J. (2012), “Transparency in complex dynamic food supply chains”, *Advanced Engineering Informatics*, Vol. 26 No. 1, pp. 55-65, doi: 10.1016/j.aei.2011.07.007.

Tsang, Y.P., Choy, K.L., Wu, C.H., Ho, G.T.S., Lam, C.H.Y. and Koo, P.S. (2018), “An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks”, *Industrial Management and Data Systems*, Vol. 118 No. 7, pp. 1432-1462, doi: 10.1108/IMDS-09-2017-0384.

Wang, Y., Sui, X., Liu, D. and Li, F. (2022), “Does logistics efficiency matter? Evidence from green economic efficiency side”, *Research in International Business and Finance*, Vol. 61, 101650, doi: 10.1016/j.ribaf.2022.101650.

Wu, J., Li, M., Zhu, Q., Zhou, Z. and Liang, L. (2019), “Energy and environmental efficiency measurement of China’s industrial sectors: a DEA model with non-homogeneous inputs and outputs”, *Energy Economics*, Vol. 78, pp. 468-480, doi: 10.1016/j.eneco.2018.11.036.

Yan, B. and Zhang, J. (2011), “Study on the efficiency of logistics industry in China based on three-stage DEA model”, *2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC)*, IEEE, pp. 3391-3394, doi: 10.1109/AIMSEC.2011.6011279.

Yu, K., Gong, R. and Wang, X. (2019), “Performance evaluation on agricultural product input/output logistics management in China”, *Custos E Agronegocio on Line*, Vol. 15 No. 3, pp. 451-459.

Yu, H., Zhao, L. and Wu, M. (2020), “Study on the evaluation of agricultural product logistics efficiency in Jilin province”, *Journal of Physics: Conference Series*, Vol. 1629 No. 1, 012061, doi: 10.1088/1742-6596/1629/1/012061.

Zhang, L.-Y., Tseng, M.-L., Wang, C.-H., Xiao, C. and Fei, T. (2019), “Low-carbon cold chain logistics using ribonucleic acid-ant colony optimization algorithm”, *Journal of Cleaner Production*, Vol. 233, pp. 169-180, doi: 10.1016/j.jclepro.2019.05.306.

Zhao, H., Liu, S., Tian, C., Yan, G. and Wang, D. (2018), “An overview of current status of cold chain in China”, *International Journal of Refrigeration*, Vol. 88, pp. 483-495, doi: 10.1016/j.ijrefrig.2018.02.024.

Zheng, W., Xu, X. and Wang, H. (2020), “Regional logistics efficiency and performance in China along the Belt and Road Initiative: the analysis of integrated DEA and hierarchical regression with carbon constraint”, *Journal of Cleaner Production*, Vol. 276, 123649, doi: 10.1016/j.jclepro.2020.123649.

Zhong, S. (2014), “The research on agricultural products logistics efficiency in China based on DEA-Malmquist model”, *Computer Modelling and New Technologies*, Vol. 18 No. 12C, pp. 1101-1106.

(The Appendix follows overleaf)

Appendix

Table A1.
List of abbreviations

Abbreviation	Full term or explanation
3PL	Third-party logistics
AHP	Analytic hierarchy process
BCC	A DEA model proposed by Banker, Charnes, and Cooper
CCR	A DEA model proposed by Charnes, Cooper, and Rhodes
CRS	Constant return to scale
DEA	Data envelopment analysis
DMU	Decision-making unit
GDP	Gross domestic product
PCA	Principal components analysis
PTE	Pure technical efficiency
SBM	Slacks-based measure
SE	Scale efficiency
SFA	Stochastic frontier analysis
TE	Technical efficiency
TFP	Total factor productivity
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
VRS	Variable return to scale

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