

Management Efficiency Improvement Plan for the Cold Chain Industry Using DEA-SBM Methodology

Hyunwoo Goh ^{1*}

¹Department of Logistics System Engineering, Seokyeong University, 02713, 124 Seokyeong-ro, Sungbuk-gu, Korea

*Corresponding author: Hyunwoo Goh, Ph. D., *Corresponding email: hwgoh@skuniv.ac.kr

HOW TO CITE:

Hyunwoo Goh (2026).
Management Efficiency
Improvement Plan for the Cold
Chain Industry Using DEA-SBM
Methodology
International Journal of Special
Education, 41(21s), 1490-1497

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.
Open access publication under the
terms and conditions
of the Creative Commons Attribution (CC BY)
license (<http://creativecommons.org/licenses/by/4.0/>).

ABSTRACT:

Objective: This study aims to present processes and strategies to improve management efficiency in the cold chain industry and secure corporate competitiveness.

Background: In Korea, the cold chain industry has established itself as a significant growth engine within the logistics sector. However, due to the technological transition to smart cold chains and chronic structural issues within the industry, the management efficiency of some firms is declining, leading to a crisis of losing competitiveness for the entire industry.

Methodology: This study applies the DEA-SBM methodology. This methodology presents a process for analyzing the causes of inefficiency by considering slack factors and setting target values for input factors subject to improvement.

Results/Conclusion: Input factors (assets, liabilities) and output factors (revenue) were selected for 12 cold chain firms. Using the DEA-SBM model, the relative efficiency of the firms was evaluated under the assumptions of CRS (Corporate Size Expansion) and VRS (Corporate Size Reduction). The causes of inefficiency were identified through SE (Corporate Size) analysis. Based on the RTS analysis, companies in an IRS state should expand their scale in the mid-to-long term, while those in a DRS state should downsize to improve management efficiency. This approach has been proven to contribute to enhancing corporate competitiveness.

Keywords: Cold chain industry, Efficiency, DEA, DEA-SBM, Input/output factors

1. Introduction

The cold chain industry is emerging as a significant growth engine in the logistics sector amidst the COVID-19 pandemic.

According to statistics from the Ministry of Food and Drug Safety (2026), the production value of

the Korean food industry is projected to reach approximately 119.7372 trillion won in 2025, a 4.3% increase from the previous year. Specifically, this figure comprises 76.7 trillion won for general foods, 40.3 trillion won for livestock products, and 2.8 trillion won for health functional foods. This demonstrates that the cold chain is more than just

a logistics market; it serves as the foundational infrastructure for the food industry, which is a major source of demand.

Furthermore, while food has traditionally been the core market for the cold chain, its scope has recently expanded to include pharmaceuticals, biotechnology, vaccines, cell and gene therapy, cosmetics, semiconductors, and precision products.

The cold chain refers to the entire supply chain that continuously maintains the temperature control required for the entire process, from product production, harvesting, pre-cooling, storage, processing, transportation, logistics centers, to sales and delivery. The Korea Cold Chain Association (KCCA) recently presented eco-friendliness, logistics AI, and AX (AI innovation) as key tasks for the industry, emphasizing that the most important technological change currently is smart cold chain.

The domestic cold chain market is expected to experience continuous growth in various studies, and according to industry forecasts, it is projected to record an average annual growth rate of approximately 9.5% from 2024 to 2031.

The problems and research objectives

The domestic cold chain industry is facing several critical issues. First is the oversupply of refrigerated warehouses. The oversupply of cold chain logistics centers has led to a decline in rental rates, resulting in increased vacancy rates and a deterioration in the return on investment. Second is high operating costs. This is the most fundamental problem facing the cold chain industry. Compared to ambient temperature logistics, additional costs are incurred for refrigeration equipment, electricity usage fees, refrigerated warehouses, refrigerated vehicles, refrigerants, insulation materials, and maintenance. Third is the urgent need to transition to eco-friendly refrigerated and frozen vehicles. In accordance with carbon neutrality policies, diesel vehicles must be converted to eco-friendly vehicles such as electric and hydrogen cars. Furthermore, the industry is also pointing out that the transition of diesel commercial vehicles to eco-friendly models under the Air Quality Management Zone Act could act as a constraint on expanding the

supply of refrigerated and frozen trucks. Fourth is refrigerant regulations: a transition from HFC refrigerants to low-GWP refrigerants, and ultimately to natural refrigerants, is necessary. Additionally, a review of the entire system, including compressors, heat exchangers, piping, and refrigerant oil, may be required. The domestic industry recognizes the costs, technology, and safety regulations associated with the transition to eco-friendly refrigerants as major challenges. Fifth, lack of cold chain standardization: The cold chain consists of various interconnected entities, including producers, transporters, logistics centers, distributors, and retailers. However, problems can arise if each firm operates temperature standards, data formats, sensors, management methods, temperature recording methods, and scopes of liability differently. Therefore, establishing standardized temperature data and history management systems will become critical in the future. Sixth, transition from 'temperature maintenance' to 'temperature data management': The smart cold chain must evolve to include temperature measurement, data storage, real-time monitoring, anomaly prediction, and history management. Seventh, shortage of skilled personnel: The cold chain is not simple logistics but requires extensive expertise. While expertise is required across the entire field, there is a severe shortage of skilled professionals in reality, necessitating the operation of separate training programs for cold chain experts. This is highly likely to become a core competitive advantage for the cold chain industry in the future. Meanwhile, the cold chain industry is characterized by large initial investment scales and a tendency for operating costs to increase gradually, acting as a factor that hinders corporate management efficiency. Consequently, corporate competitiveness is declining. Unlike the existing DEA methodology, this study utilizes the DEA-SBM methodology to conduct efficiency evaluation and analysis that considers the margins of input factors. Through this, the study aims to contribute to strengthening corporate competitiveness by practically analyzing corporate management efficiency and proposing improvement measures.

Literature Review

There is little research related to this topic, and GOH, H. (2024) is the only one; he evaluated and analyzed the efficiency of firms using the DEA technique. He selected 'Liabilities' and 'Capital' as input factors and 'Sales' and 'Operational Profit' as output factors, and evaluated the relative efficiency of 17 firms using CCR and BCC models. In addition, he identified the causes of inefficient firms and suggested goal setting and improvement directions to reduce the ap with efficient firms.

Theoretical Background

Existing models in DEA, such as CCR and BCC, have the disadvantage of failing to consider both input and output simultaneously by fixing only one of the input or output elements and classifying them as either input-oriented or output-oriented. To overcome this limitation, SBM, which incorporates slack into its formula, can consider both input and output at the same time.

As shown in the 1 input-1 output graph in Figure 1, the distance from point E ($1-X/(1-Y)$) that minimizes the decrease in input (X) and the increase in output (Y) in the SBM model serves as the measure of efficiency.

In this case, a measure of '1' appears when both slack X and Y are '0', and the point is determined to be at the efficiency boundary.

Since it is an input-oriented model, the output slack at point E cannot be controlled; therefore, only the input slack is adjusted, and the distance from A is used as the measure of efficiency.

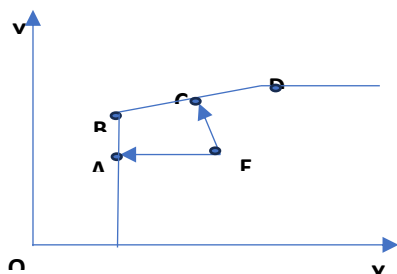


Figure 1. 1 input - 1 output

Figure 2 is a 2 input-1 output graph, which

illustrates the non-radial characteristics of the SBM model. In the case of a radial model, D and E are adjusted at the same rate to reduce inputs and move toward the origin(O) along the efficiency frontier. This method has the problem of requiring the reduction of two or more inputs with different units at the same rate. But the SBM model adjusts the two inputs at separate rates by reducing input X_2 to C and input X_1 to B based on E. This differs from the existing radial model, which radiates from the origin.

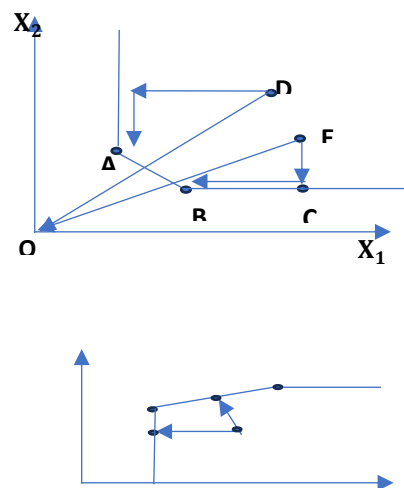


Figure 2. 2 input - 1 output

2. Methodology

Design

The study subjects (DMUs) for the analysis of management efficiency are selected as 12 firms belonging to the cold chain industry listed on the Korea Exchange (divided into the Korea Composite Stock Price Index (KOSPI) and the Korea Securities Dealers Automated Quotation Index (KOSDAQ)) in 2025. To analyze efficiency, candidate input/output factors are identified, data is collected, and final input/output factors are selected through correlation analysis. Additionally, the appropriateness of the number of DMUs and the number of input/output factors is reviewed. Subsequently, the management efficiency of the firms is evaluated and analyzed using the DEA-SBM technique, and goals and measures for improving the efficiency of inefficient firms are analyzed.

Research instrument

The DEA-SBM methodology is applied as a tool to evaluate and analyze the relative efficiency of cold chain firms, and DEA-Solver version 14 software is used for data processing.

Procedure and data processing

To analyse management efficiency, objective and quantitative candidate input and output factors were selected by referring to financial statement data and previous studies. Accordingly, assets, liabilities, and capital were selected as candidate input factors, and sales, operational profit, and net profit were selected as candidate output factors; data were then collected from the financial statements of each firm, which represent their management status. Correlation analysis was conducted among the candidate factors, and those with high correlations between input and output factors and relatively low multicollinearity among input factors were selected as the final factors. Assets and liabilities were finally determined as the input factors, and sales as the output factor; the correlations are shown in Table 1, and the statistics for these input and output factors are presented in Table 2.

Table 1. Correlation of Input/Output Factors

	Assets	Liabilities	Sales
Assets	1	.735**	.821**
Liabilities		1	.884**
Sales			1

** . The correlation is significant at the 0.01 level (two-sided).

Table 2. Descriptive Statistics of Input/Output Factors

(unit: hundred million won)

Factor	Input		Output
	Assets	Liabilities	Sales
Statistics			

Max	4,012	3,150	6,298
Min	686	38	145
Average	1,930	771	1,332
SD	1,152	782	1,732

Meanwhile, in DEA, assuming the number of input elements = m, the number of output elements = s, and the number of DMUs = n, if the number of DMUs is too small, a problem arises where most DMUs are efficiently judged. Therefore, Cooper, Seiford & Tone (2007) suggested a recommended minimum number of DMUs as $n \geq \max \{m \times s, 3(m + s)\}$. In this study, $12 \geq \max \{2 \times 1, 3(2 + 1)\} = 9$, satisfying the recommended minimum criterion.

3. Results

The results of the efficiency evaluation of 12 cold chain firms using the DEA-SBM model are shown in Table 3.

Efficiency Analysis:

First, the analysis of the DEA-SBM model under the CRS (constant returns to scale) assumption revealed that the efficiency of cold chain firms averaged 45.2%. DMUs D05 and D10 had an efficiency value of '1', indicating that only two DMUs were efficient, while the remaining DMUs were inefficient. An efficiency value of '1' signifies 100% efficiency. Conversely, the firms with the lowest relative efficiency were DMUs D08 and D12, each with an efficiency of 16%. An efficiency value of 0.160 indicates that the efficiency is 16% of that of the efficient frontier.

Second, the analysis of the DEA-SBM model under the assumption of Variable Returns to Scale (VRS) revealed that the average efficiency of cold chain firms was 59.0%. This implies that only the three DMUs (D01, D05, and D10), with an efficiency value of '1', are efficient, while the remaining DMUs are inefficient. On the other hand, DMU D11, with an efficiency value of 27.4%, is the firm with the lowest relative efficiency. An efficiency value of 0.274 indicates that its efficiency

is 27.4% relative to the efficient frontier.

SE and RTS Analysis:

First, Scale Efficiency (SE) is an indicator that evaluates whether a DMU operates at the most efficient production scale.

SE can be expressed using the efficiency values from the CRS and VRS assumptions in the DEA-SBM model. That is, it is calculated as $SE = CRS / VRS$. Here, if SE is '1', it indicates complete optimization. If SE is less than '1', you can analyze the cause of inefficiency under the CRS assumption to determine whether the inefficiency occurs in VRS or SE.

① When $CRS < 1$ and $VRS = 1$; VRS has an efficiency of 100%, but SE is inefficient, so it can be analyzed that the current operating scale is not the optimal scale. DMUs D01 and D07 in Table 3 correspond to this.

② When $CRS < 1$, $VRS < 1$, and $SE = 1$; SE is

the optimal scale, but it can be analyzed that the cause of inefficiency is attributed to VRS.

③ When $CRS < 1$, $VRS < 1$, and $SE < 1$; it can be interpreted that the cause of inefficiency exists in both VRS and SE. DMUs D02, D03, D04, D06, D08, D09, D11, and D12 in Table 3 correspond to this.

Second, returns to scale (RTS) is a concept representing the change in output resulting from an increase in input factors, and it is an important indicator for judging the efficiency of production scale.

SE takes a value between 0 and 1; if SE is 1, it means that the DMU is in the CRS state, which is the optimal scale level. On the other hand, if $SE < 1$, it is necessary to further investigate why the scale is inefficient. That is, it means that the DMU is in an increasing return to scale (IRS) or decreasing return to scale (DRS) state.

Table 3 Results of the DEA-SBM Model

DMU	DEA-SBM			
	CRS	VRS	SE	RTS
D01	0.456	1	0.456	IRS
D02	0.242	0.306	0.790	IRS
D03	0.256	0.279	0.919	IRS
D04	0.513	0.528	0.972	IRS
D05	1	1	1	CRS
D06	0.223	0.294	0.757	IRS
D07	0.804	1	0.804	DRS
D08	0.160	0.477	0.335	IRS
D09	0.381	0.444	0.859	DRS
D10	1	1	1	CRS
D11	0.234	0.274	0.854	IRS
D12	0.160	0.477	0.335	IRS
AVE	0.452	0.590	0.757	

Directions for Improving Efficiency

we benchmark the efficient DMUs to establish

improvement goals for their input elements. In particular, DEA-SMB is used to derive realistically achievable improvement goals for each input element. The causes of inefficiency and the factors to prioritize for efficiency improvement can be identified by analyzing the slack time of each element. Furthermore, improvement goals can be set by classifying the efficiency of each input element for inefficient DMUs using SBM(CRS) and SBM(VRS) models.

Table 4 shows the results of the SBM efficiency analysis and the slack for each element. In Table 4, 'Data' refers to the current value, 'Projection' refers to the improvement target value (slack), and 'Diff (%)' refers to the percentage difference between 'Data' and 'Projection'.

Improvement Directions by Input Factor:

The average slack of SBM(CRS) for Assets, the input factor, is 53%. In particular, DMUs D01, D06, D11, D12, D08, D03, D02, and D09 are DMUs with slacks significantly larger than the average and are therefore targets for focused improvement. The average slack of SBM(VRS) is 30.3%. In particular, DMUs D03, D11, D06, D02, D09, and D04 are DMUs with slacks significantly larger than the average and are therefore targets for focused improvement. The average slack of SBM(CRS) for the input factor Liabilities is 56.5%. In particular, DMUs D12, D08, D02, D11, D06, D03, and D09 are DMUs with slacks significantly larger than the average and are designated as

priority improvement targets.

The average slack of SBM(VRS) is 51.7%. In particular, DMUs D12, D08, D02, D11, D03, D06, D09, and D04 are DMUs with slacks significantly larger than the average and are designated as priority improvement targets.

Improvement Directions for Individual firms:

improvement goals for each input factor must be set from the perspective of inefficient firms that do not have a slack of '0'. That is, to improve an inefficient DMU from the perspective of an individual firm, the current value ('data') for each input factor must be reduced by the slack ('Difference (%)') to the target value ('projection').

For example, in Table 4, for the inefficient DMU D02 to become an efficient DMU, under the assumption of CRS, the input factor Assets must be reduced by 62.4% from the current 1,418 (hundred million won) to the target value 533 (hundred million won), and at the same time, another input factor Liabilities must be reduced by 89.2% from the current 1,058 (hundred million won) to the target value 114 (hundred million won).

In previous studies, the improvement goals for each DMU were all the same. This had the problem of being unrealistic. However, in DEA-SBM, the improvement goals for each DMU were different, and if the DMUs with the largest range of improvement were selected as a priority, the average of all DMUs could be dramatically improved.

Table 4 Summary of Improvement goals for Input Factors applying DEA-SBM

(unit: hundred million won)

DMU	Assets					Liabilities				
	Data	CRS		VRS		Data	CRS		VRS	
		Proj.	Diff.(%)	Proj.	Diff.(%)		Proj.	Diff.(%)	Proj.	Diff.(%)
D01	686	129	-81.2	686	0	38	28	-27.5	38	0
D02	1,418	533	-62.4	711	-49.9	1,058	114	-89.2	117	-88.9
D03	2,287	620	-72.9	716	-68.7	548	132	-75.9	134	-75.6
D04	1,188	686	-42.2	720	-39.4	327	146	-55.2	147	-55.0

D05	722	722	0	722	0	154	154	0	154	0
D06	2,103	432	-79.5	704	-66.5	384	92	-76.0	97	-74.7
D07	3,863	3,091	-20.0	3,863	0	817	659	-19.3	817	0
D08	799	196	-75.5	690	-13.6	564	42	-92.6	51	-90.9
D09	3,037	1,473	-51.5	1,718	-43.4	1,133	314	-72.3	364	-67.8
D10	4,012	4,012	0	4,012	0	3,150	3,150	0	3,150	0
D11	2,244	546	-75.7	711	-68.3	519	116	-77.6	120	-77.0
D12	799	196	-75.5	690	-13.6	564	42	-92.6	51	-90.9
AVE.	1,930	1,053	-53.0	15,943	-30.3	771	416	-56.5	437	-51.7

4. Discussion

In the efficiency analysis of the previous section, the efficiency value of DEA-SBM (VRS) was found to be 13.8% higher than that of DEA-SBM (CRS). This is because the CRS assumption assumes that the DMU operates at an optimal scale, whereas the VRS assumption evaluates the efficiency best suited for the DMU regardless of the DMU's size. Since the firms subject to this study exhibit significant variations in their inputs—assets and liabilities—the analysis under the VRS assumption, which reflects differences in scale, appears more valid.

DMUs with efficiency below 100% should benchmark against DMUs with 100% efficiency to improve their efficiency.

Through SE analysis, we were able to identify the causes of scale efficiency and inefficiency within the DMU. Furthermore, RTS analysis allowed us to determine the specific reasons for scale inefficiency once it was detected. Summarizing the research process to date, the efficiency evaluation and analysis procedure can be established as follows: If $TE < 1$ for a DMU, Step 1: Verify PTE via BCC; Step 2: Calculate $SE = TE/PTE$; Step 3: $PTE = 1, SE < 1 \rightarrow$ Scale inefficiency; $PTE < 1, SE = 1 \rightarrow$ Pure technical inefficiency; $PTE < 1, SE < 1 \rightarrow$ Technical + scale inefficiency; Step 4: If $SE < 1$, verify RTS; $IRS \rightarrow$ Need for scale expansion; $DRS \rightarrow$ Need for scale reduction.

In the direction of improvement for each element of the cold chain industry, it can be seen that for both input factors, assets and liabilities, the average slack of SBM (CRS) is greater than the average slack of SBM (VRS). This means that when considering the input margin, the range to be reduced under the CRS assumption is greater.

Comparing the average slacks of SBM(CRS) and SBM(VRS) for Assets and Liabilities, it can be seen that Liabilities are the most important factor to consider for efficiency improvement in the cold chain industry.

Limitations:

This study has limitations in that the number of firms listed on the KRX may vary depending on the time of the study. Additionally, input/output factors may fluctuate, making pairwise comparisons between survey times difficult.

5. Conclusion

This study evaluated and analyzed management efficiency to enhance the competitiveness of the cold chain industry. Input factors (assets, liabilities) and output factor (sales) were selected for 12 firms, and the relative efficiency of the firms was evaluated under CRS and VRS assumptions using the DEA-SBM model. Under the CRS assumption, two firms were efficient, while under the VRS assumption, four firms were efficient. To identify the causes of inefficiency, SE analysis and RTS analysis were conducted to determine whether the cause lay in SE, efficiency under the VRS

assumption, or both. Through RTS analysis, eight firms were identified as being in an IRS state, two as being in a CRS state, and two as being in a DRS state. It was proposed that in the medium to long term, firms in the IRS state should expand their scale, while firms in the DRS state should reduce their scale to improve management efficiency.

Directions for inefficient firms to improve efficiency by benchmarking against efficient firms were presented under CRS and VRS assumptions. The DEA-SBM model was used for the study, and it was noted that prioritizing the improvement of liabilities with large average slack among input factors is the direction for the entire cold chain

industry.

Meanwhile, specific improvement targets were presented under CRS and VRS assumptions for inefficient individual firms to become efficient.

This study demonstrated the process of improving management efficiency in the cold chain industry, and it is expected that the industry's competitiveness will be established through periodic evaluation and analysis.

Since the number of firms included in the cold chain industry group may fluctuate in the future, continuous research on this is necessary.

6. References

- Banker, R. D., Charnes, A. & Cooper W. W. (1984). Some Models for Estimating technical and Scale Efficiencies in Data Envelopment Analysis. *Management Science*, 30, 1490-1497.
- Charnes, A., Cooper, W. W. & Rhodes, E. (1978). Evaluating Program and managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through. *Management Science*, 27(6), 1490-1497.
- Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. New York, Springer.
- Farrell, M. J. (1957). The Measurement of productivity efficiency. *Journal of the Royal Statistical Society*, 120(3), 1490-1497.
- GOH, H. (2024). Evaluation of Management Efficiency in the Cold Chain Industry using DEA Techniques, *International Journal of Religion*, 5(10), 4870–4878. <https://doi.org/10.61707/dehz0476>.
- Tone Kaoru (2001). A slack-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130, 1490-1497.

7. Acknowledgements

This research was supported by Seokyeong University in 2025.

8. Author Declaration

The authors confirm that this research is an original work and has not been published in any way. The authors have no potential conflicts of interest to declare.