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Study on Relative Efficiency Evaluation of Broiler Companies using DEA Model

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Abstract

This study was conducted to evaluate the management efficiency of broiler companies. First, the efficiency of the target companies was categorized into technical efficiency and pure technical efficiency and ranked. Second, the amount of efficiency that can be improved by inefficient companies was calculated. Third, the causes of inefficiency were analyzed from the perspective of scale and operation. For this purpose, the DEA model was used and an analysis system to increase management efficiency in the broiler industry was empirically presented.

Keywords: *Broiler Industry, Covid-19 Pandemic, Relative Efficiency, Data Envelopment Analysis (DEA).*

INTRODUCTION

In Korea, the global COVID-19 pandemic has resulted in increased risk aversion, such as decreased investment by economic entities and entry of new companies, differentiation between industries, and excessive liquidity. This continued after the global financial crisis and served to deepen the slowdown in productivity and decline in dynamism. The slowdown in productivity led to a decline in the potential growth rate and an increase in the risk aversion of economic entities, which lowered the equilibrium interest rate level of the Korean economy and resulted in a prolonged period of ultra-low interest rates. Therefore, the need for tax reform to secure fiscal soundness in order to stabilize the macroeconomy has increased. As such, the COVID-19 pandemic has brought many changes not only to the economy but also to many other areas, including society and culture.

The uncertainty caused by the pandemic in the industry also affected the broiler industry. As the development and supply of vaccines normalize, expectations for 'with covid-19', a gradual recovery of the domestic economy, a 52-hour work week, the holding of the Tokyo Summer Olympics, and the revitalization of delivery culture due to non-face-to-face, etc. Consumption has increased. However, periodic pandemics have delayed the transition to daily life, and the continued outbreak of highly pathogenic AI has also affected chicken consumption. Due to international increases in labor costs and incidental costs, the production cost of chicken has risen slightly, and with the designation of a new export workshop in Brazil, chicken imports have increased in 2021.

After the COVID-19 pandemic, in this internal and external environment, broiler companies need to develop a variety of products to reflect the needs of expanded chicken consumption promotion, changes in dietary trends from snacks to main meals and side dishes, and changes in non-contact consumption patterns. Therefore, efforts must be made to produce high-quality chicken to increase self-sufficiency and increase consumption to survive competition from the influx of imported chicken and lay the foundation for a sustainable industry. In other words, efforts to increase management efficiency are required to respond to threats. In this regard, Kim, J. B. (2021) selected 21 companies as targets and used data from 2019. The input variables were debt ratio and liquidity ratio, and the output variables were operating profit ratio and asset growth rate to analyze the efficiency of broiler companies. However, the study was conducted the year before the COVID-19 pandemic, so the timing is not appropriate, which reduces the value of the study. Thus, research on changes in the efficiency of broiler companies after COVID-19 is necessary.

Therefore, the purpose of this study is to evaluate and analyze the management efficiency of companies to develop the broiler industry after COVID-19 and provide an evaluation basis to improve competitiveness.

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Concept of DEA

Efficiency can be defined as the ratio of output to input, and is a measure of how much output is generated at a certain cost or how much cost is invested to obtain a certain output. In addition, efficiency is divided into absolute efficiency and relative efficiency. Absolute efficiency is expressed as a physical unit or some kind of ratio, while relative efficiency is a value expressed relative to the highest level of efficiency among economic entities engaged in production activities.

Farrell's (1957) change efficiency, which is based on relative efficiency, can measure not only input-to-output efficiency, but also both input-to-output efficiency and quality efficiency using indicators related to results and quality. Farrell (1957) believed that the relative efficiency of each decision making unit (DMU) can be measured in relation to the frontier efficiency that efficient DMUs empirically form. So he proposed the data envelopment analysis (DEA) model.

The DEA model can be divided into the CCR model of Charnes et al. (1978) and the BCC model of Banker et al. (1984). The difference between the two models is that the basic assumptions underlying the production relationship between input and output factors are different. In other words, the CCR model assumes constant return to scale (CRS), which means that output factors increase at a constant rate when input factors are increased at a certain rate, while the BCC model assumes variable returns to scale (VRS) and increases input factors at a certain rate.

It is assumed that the output factor does not increase at a constant rate when increased at a constant rate. These two models are divided into input-oriented and output-oriented depending on which element they focus on input or output. In the input-oriented model, the direction of efficiency improvement is to minimize input factors, while in the output-oriented model, the direction of efficiency improvement is to maximize output factors. Since the purpose of this study focuses on input factors, we will examine the formula focusing on the input-oriented CCR model and the input-oriented BCC model.

In the case of the input-oriented CCR model, under the premise that the kth observation belongs to the production possibility set, the degree of efficiency (k) of this observation is expressed as the ratio that can reduce input to the maximum while keeping output fixed, as shown in Equation (1) can be presented

$$\theta^{k^*} = \min_{\theta,\lambda} \theta^k \tag{1}$$

subject to

$$\theta^k x_m^k \geq \sum_{j=1}^{J} x_m^j \lambda^j \qquad (m = 1,2,\dots,M);$$

$$y_n^k \leq \sum_{j=1}^{J} y_n^j \lambda^j \qquad (n = 1,2,\dots,N);$$

$$\lambda^j \geq 0 \qquad (j = 1,2,\dots,J)$$

On the other hand, the input-oriented BCC model is presented as equation (2), and the condition ($\sum_{j=1}^{J} \lambda^j = 1$) is added to equation (1). Because of this condition, infinite reduction or expansion of observations or points combining observations into linear division is not allowed. Instead, only points that satisfy internal division and free disposability between observations are recognized as being producible.

$$\theta^{k^*} = \min_{\theta,\lambda} \theta^k \tag{2}$$

subject to

$$\theta^k x_m^k \geq \sum_{j=1}^{J} x_m^j \lambda^j \qquad (m = 1,2,\dots,M);$$

$$y_n^k \leq \sum_{j=1}^{J} y_n^j \lambda^j \qquad (n = 1,2,\dots,N);$$

$$\sum_{j=1}^{J} \lambda^j = 1 ;$$

$$\lambda^j \geq 0 \qquad (j = 1, 2, \dots, J)$$

On the other hand, the efficiency of a production unit (firm) can be calculated by measuring the distance the production unit is from an efficient set of input or output spaces. This is called technical efficiency (TE) and represents the ability of a production unit to obtain maximum output from specific inputs. TE is measured using the CCR model assuming constant returns to scale (CRS) of the production function, and pure technical efficiency (PTE) is measured using the BCC model assuming VRS of the production function.

In addition, although the DEA model is an econometric model, it does not need to assume a specific production function form, and multiple input and output factors can be included in the model. As a result, in terms of utilization, it has the advantage of being able to easily identify who is being benchmarked and the gap.

Concept of Dea

Research Target and Scope

The subjects of this study are nine broiler companies listed on Korea Exchange (KRX) and evaluate their relative efficiency for 2023. The input and output factors required for the DEA method utilize the company's published financial statements. We look at industries where cold chains exist in Korea and their characteristics.

Data Collection and Determination of Input/Output Factors

In the financial statements announced in 2023, assets, liabilities, and capital are selected as candidates for input factors, and sales, operating profit, and net profit are selected as candidates for output factors, and data are collected.

The correlation between input and output factors is analyzed for candidate factors, multicollinearity between input factors is analyzed, and input/output factors are finally determined.

DEA Model Application and Analysis

Apply the CCR-I and BCC-I models to the collected data to evaluate input-oriented technical efficiency (TE) and input-oriented pure technical efficiency (PTE).

Through ranking analysis, we rank the relative efficiency between companies and identify benchmarking targets for inefficient companies.

Through analysis of improvement targets, inefficient companies benchmark efficient companies and set the difference in input factors as improvement goals.

Through scale efficiency (SE) analysis, we analyze the efficiency of optimization for scale. It also identifies the causes of inefficiency.

Empirical Analysis Results

In order to analyze the management efficiency of 9 broiler companies that are DMUs, the results of empirical analysis using descriptive statistics analysis and DEA model for input and output factors in 2023 are as follows.

Descriptive Statistics of Input and Output Factors

The input and output factors of the 9 broiler companies in 2023 were selected as liability, capital, sales, and operating profit, and their descriptive statistics are shown in <Table 1>.

Table 1. Descriptive Statistics of Input/Output Factors

(unit : hundred million won)

Factor \ Statistics	Liabilities	Capital	Sales	Operational Profit
Max	5220	3851	13774	398

Min	397	321	1012	-122
Average	2355	1806	6261	170
SD	2045	1221	5348	167

Efficiency Analysis

Input-oriented technical efficiency can be analyzed with the CCR-I model, and input-oriented pure technical efficiency can be analyzed with the BCC-I model.

Input-Oriented Technical Efficiency (TE)

The calculated efficiency is between '0' and '1'. If the value is '1', the DMU has reached the efficient frontier, and if the value is less than '1', it is evaluated as inefficient. Four DMUs (D05, D06, D08, D09) are efficient and five DMUs (D01, D02, D03, D04, D07) are inefficient. The rankings were evaluated in descending order of efficiency, and the average technical efficiency of the 9 DMUs was 0.77, and the minimum was 0.317 in D07(<Table 2>).

Table 2. Summary of input-oriented technical efficiency

DMU	Score	Rank	Reference(Lambda)								Reference count
D01	0.530	8	D06	(0.111)	D09	(0.130)					
D02	0.716	5	D05	(0.834)	D08	(0.242)	D09	(1.534)			
D03	0.716	5	D05	(0.834)	D08	(0.242)	D09	1.534			
D04	0.645	7	D05	(0.265)	D08	(0.043)					
D05	1	1	D05	(1.000)							3
D06	1	1	D06	(1.000)							2
D07	0.317	9	D06	(0.510)	D09	(0.132)					
D08	1	1	D08	(1.000)							3
D09	1	1	D09	(1.000)							4

Input-Oriented Pure Technical Efficiency (PTE)

Six DMUs (01, D04, D05, D06, D08, D09) are efficient and three DMUs (D02, D03, D07) are inefficient. The rankings were evaluated in descending order of efficiency, and the average pure technical efficiency of the 9 DMUs was 0.93, and the minimum was 0.381 in D07(<Table 3>).

Table 3. Summary of input-oriented pure technical efficiency

DMU	Score	Rank	Reference(Lambda)								Reference count
D01	1	1	D01	(1.000)							1
D02	0.984	7	D08	(0.979)	D09	(0.021)					
D03	0.984	7	D08	(0.979)	D09	(0.021)					
D04	1	1	D04	(1.000)							
D05	1	1	D05	(1.000)							
D06	1	1	D06	(1.000)							1

D07	0.381	9	D01	(0.421)	D06	(0.524)	D09	(0.055)	
D08	1	1	D08	(1.000)					2
D09	1	1	D09	(1.000)					3

Improvement Target Value Analysis

The purpose of efficiency evaluation is to improve the efficiency of inefficient DMUs. DMUs evaluated as inefficient refer to efficient DMUs that form similar input combinations. <Table 2> and <Table 3> summarize the reference sets and reference counts. Among efficient DMUs, DMUs with a high number of references form similar input combinations to inefficient DMUs, so they can be used as targets for benchmarking. Meanwhile, DMUs that have been efficiently evaluated but have a small number of references are inadequate as benchmarking targets because they are likely to be formed from heterogeneous input combinations.

The improvement target values for technical efficiency and pure technical efficiency are shown in <Table 4> and <Table 5>, respectively. In the table, 'Data' refers to the current value, 'Projection' refers to the improvement target value, and Diff(%) refers to the percentage difference between 'Data' and 'Projection'. For example, DMU D01 in <Table 4> is inefficient, and in order to become an efficient DMU, the input factor 'Liabilities' must be reduced by 47% from the current 394 to 211, and another input factor 'Capital' must be reduced by 47% from 664 to 352.Input-oriented technical efficiency can be analyzed with the CCR-I model, and input-oriented pure technical efficiency can be analyzed with the BCC-I model.

Table 4. Target value for improvement of technical efficiency

(unit: hundred million won)

DMU	Liabilities			Capital		
	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	397	211	-47.0	664	352	-47.0
D02	5,215	3,736	-28.4	3,007	2,154	-28.4
D03	5,215	3,736	-28.4	3,007	2,154	-28.4
D04	795	513	-35.5	321	207	-35.5
D05	1,089	1,089	0	472	472	0
D06	697	697	0	2,177	2,177	0
D07	1,544	490	-68.28	3,851	1,221	-68.3
D08	5,220	5,220	0	1,908	1,908	0
D09	1,021	1,021	0	847	847	0

Table 5. Target value for improvement of pure technical efficiency

(unit : hundred million won)

DMU	Liabilities			Capital		
	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	397	397	0	664	664	0
D02	5,215	5,130	-1.6	3,007	1,885	-37.3
D03	5,215	5,130	-1.6	3,007	1,885	-37.3
D04	795	795	0	321	321	0
D05	1,089	1,089	0	472	472	0

D06	697	697	0	2,177	2,177	0
D07	1,544	588	-61.9	3,851	1,467	-61.9
D08	5,220	5,220	0	1,908	1,908	0
D09	1,021	1,021	0	847	847	0

Scale Efficiency (SE) Analysis

In the production relationship between input and output factors, efficiency through optimization of scale related to the production capacity of the production entity can be examined, which is called scale efficiency (SE).

Scale efficiency can be calculated by dividing technical efficiency (TE), which is the efficiency of the CCR model, by pure technical efficiency (PTE), which is the efficiency of the BCC model (<Table 6>).

And if SE is '1', it is full scale optimization, if PTE>SE, the cause of inefficiency is SE, and if PTE<SE, the cause of inefficiency can be interpreted as PTE.

Four DMUs(D05, D06, D08, D09) demonstrate the efficiency of a completely optimal scale, and among the inefficient DMUs, PTE is the cause of inefficiency in D07, and SE is the cause of inefficiency in the remaining inefficient DMUs.

Table 6. Scale efficiency (SE) and cause of inefficiency

DMU	efficiency score		SE	cause of inefficiency	
	CCR(TE)	BCC(PTE)		PTE	SE
D01	0.530	1	0.530		o
D02	0.716	0.984	0.728		o
D03	0.716	0.984	0.728		o
D04	0.645	1	0.645		o
D05	1	1	1		
D06	1	1	1		
D07	0.317	0.381	0.832	o	
D08	1	1	1		
D09	1	1	1		

CONCLUSION

This study was conducted to evaluate the management efficiency of the broiler industry, which has benefited the most among the food industry as the delivery industry in Korea became more active during the COVID-19 pandemic. Input and output factors were derived for 9 broiler companies in 2023 and analyzed by dividing them into technical efficiency and pure technical efficiency. DEA was applied as a methodology for this purpose. First, the efficiency of companies was evaluated by analyzing efficiency rankings. Second, benchmarking targets were identified and target values for inputs that inefficient companies need to improve were calculated. Third, through scale efficiency analysis, the causes of inefficiency in inefficient companies were identified.

We hope that the process of this study will be used as a way to improve the efficiency of companies, and once data for the next few years is secured, research on changes in efficiency during the COVID-19 pandemic and the same period thereafter is necessary.

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