Using DEA Model to Evaluates the Operational Efficiencies of Taiwan’s Food Companies

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Abstract

This study assesses the efficiency of ESG practices and operational performance of Taiwan's food processing companies. Using data from 26 listed firms from 2018 to 2023, the research incorporates key measures such as the number of employees, employee benefits and wages, operating costs, operating expenses, operating revenue, and ESG scores. The Super-SBM (Slack-Based Measure) model and the Malmquist Productivity Index (MPI) are applied to evaluate efficiency and productivity changes over the research period. The results reveal significant efficiency gaps among companies and identify areas with improvable slacks. The MPI analysis indicates fluctuating productivity, influenced by external shocks like the COVID-19 pandemic and the Russia–Ukraine war. Findings suggest that dynamic transformations and robust ESG integration are essential for enhancing resilience and competitiveness in the food industry.

Keywords: Food companies, ESG, , DEA, Super-SBM, Malmquist Productivity Index, Taiwan

1. Introduction

1.1 Research Background

Food is indispensable in daily life, so it is obvious that the food industry plays a significant role in sustaining human life and driving economic growth. With the global population surpassing eight billion people and ever-growing, this sector is irreplaceable and will continue to expand in the future. The United Nations Environment Program (UNEP) emphasizes that “the demand for food is projected to increase by 60 percent by 2050.” This means that we should be more cautious about the actions we take today and take a further look in the future when food security, environment, economy, health, education, peace, and human rights will be affected heavily. (United Nations Environment Program [UNEP], 2021, para. 8)

Table 1: 2023 Food Industry by channel ($ billion)

Food and Agricultural Exports	$5.9
Food Processing	$30
Retail	$9.8
Food Service	$32.6

Source: Department of Statistics, Taiwan Ministry of Economic Affairs; Ministry of Agriculture; International Monetary Fund, as cited in U.S. Department of Agriculture (USDA) Taiwan Food Processing Ingredients Annual Report (2024).

This research will focus on the food processing sector, which accounts for a big proportion of the food industry and has an enormous impact on forming consumer food choices, influencing supply chain dynamics, and driving technological advancements, followed by various consequences of social, health and environmental problems, climate change and ecological balance corruption.

Statistics of 2022 showed that there are 7,285 operating factories in Taiwan and more than 200,000 employees working in the food industry and the number is rising (Department of Statistics, Ministry of Economic Affairs, 2022). Currently, Taiwan has 29 listed food companies that contribute significantly to the country's production output. Although the profits these companies generate are substantial, we must still closely examine the environmental issues associated with these businesses.

As food production scales up to meet rising demand, the industry's environmental footprint grows correspondingly. Notarnicola et al. (2012) identified several environmental threats associated with rising food demand, including land use changes, soil quality degradation, loss of biodiversity, pesticide exposure, and increasing genetically modified foods (Notarnicola et al., 2012). These threats can be seen more clearly in Poore & Nemecek (2018) data set (Figure 1), which shows how big are the negative impacts of food supply chain on the environment.

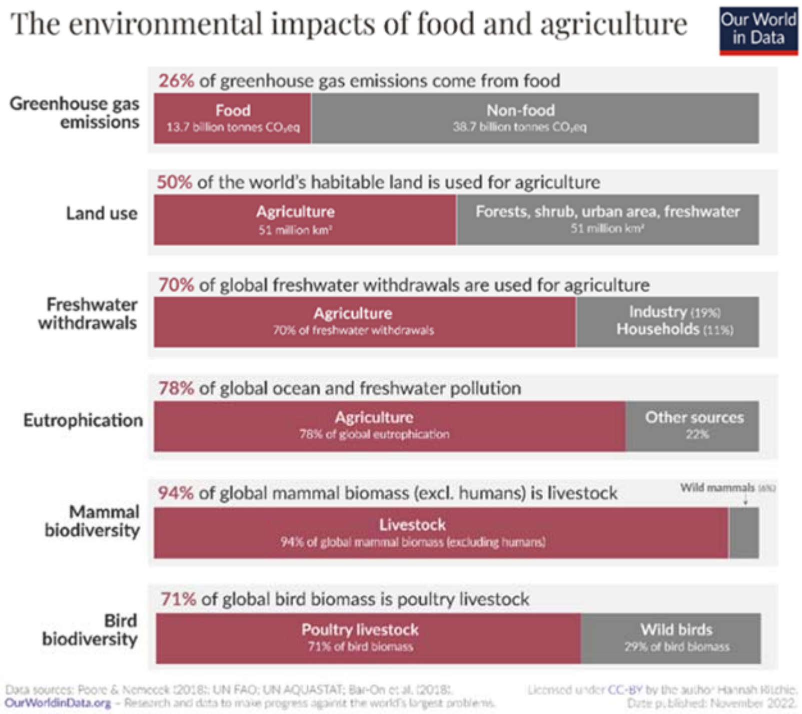

Figure 1: The environmental impacts of food and agriculture

Source: Poore & Nemecek (2018).

1.2 Research Motivation

The growing significance of Environmental, Social, and Governance (ESG) practices in the business world, especially within the food processing sector, has sparked interest in understanding how these sustainable initiatives influence operational performance. In Taiwan's food processing industry, integrating ESG factors has become crucial due to increasing regulatory pressures, consumer demand for sustainable products, and the need to maintain a competitive edge in the global market. This study is motivated by the need to understand whether sustainable business practices can lead to better outcomes in terms of productivity and ESG performance.

Integrating sustainability into core business practices can encourage firms to innovate, optimize resource use, and reduce waste and then help firms make measurable improvements in operational efficiency. Consequently, the research will contribute to decision-making for food processing businesses aiming to improve productivity while meeting sustainability goals.

1.3 Research Objectives

The primary objective of this study is to evaluate the operational efficiency of ESG practices in Taiwan's food industry, which include 29 listed companies, utilizing the Super-SBM (Slack-Based Measure) model and the Malmquist Productivity Index. These advanced DEA techniques allow for a more comprehensive evaluation of input slacks targeting to make actual ESG performance optimization overtime.

Additionally, the research also seeks to provide strategic recommendations to help food processing companies better align operational practices—such as resource allocation, labor structure, and cost management—with ESG principles. By doing so, it offers insights into how sustainability initiatives can drive improvements in both operational efficiency and ESG outcomes.

2. Literature Review

Data Envelopment Analysis (DEA) was optimized from the original productive efficiency measure method, which was a single-output/single-input approach developed by Farrell (1957). DEA was first developed by Charnes, Cooper and Rhodes (1978), known as CCR model based on constant returns to scale, which assumes that any change in inputs should produce a proportionate change in outputs. Later in 1984, Banker, Charnes and Cooper extended it to include variable returns to scale and named it BBC model, which is different from the CCR model where the proportionate increase in outputs does not necessarily equal the proportionate increase in inputs.

In the food industry, numerous studies have employed DEA method to measure efficiency. For instance, the researchers apply DEA to evaluates the efficiency of the Mexican food industry (Flegl et al., 2022), the performance of Indian meat processing industry (Ali, 2007), the innovation ability of Taiwan's food industry (Dadura & Lee, 2011), R&D performance in the Chinese food manufacturing industry to reduce investment risk (Mao et al., 2022) and many other studies.

When evaluating sustainability practices, ESG is the most comprehensive framework because it addresses existing shortcomings by integrating distinct management processes and offering a holistic approach to sustainability reporting and decision-making (Whitelock, 2019). ESG factors also encompass undesirable outputs, such as greenhouse gas emissions, waste, and pollution, which need to be minimized (Gomes & Lins, 2008). These factors are crucial for assessing the environmental impact of the food processing industry.

Table 2: List of studies using DEA to evaluate food firms' sustainability efficiency

Authors	Scope of study	Research design	Input	Output	Dimension
Egilmez et al. (2014)	Supply chain sustainability assessment of 33 food manufacturing companies in US	EIO-LCA (Life Cyle Assessment) and DEA	Carbon footprint Water withdrawals Energy footprint Cropland footprint Grazing land footprint Forest land footprint Fishery land footprint	Supply Chain Decomposition Analysis	Environment
Zhang et al. (2021)	Measure efficiency and Environmental Sustainability of top 10 countries in the global agricultural production	Entropy-DEA Model	Labor force Agricultural arable land area Agricultural irrigation area Agricultural machinery Fertilizer consumption.	Agricultural GDP CO2 emission (undesirable)	Environment Social
Vaez-Ghasemi et al. (2022)	Cost efficiency of sustainable supply chains of 15 tomato paste supply chains within the food industry in Iran.	DEA Model	Raw materials Staff Water usage Inter-products	Green products CO2 emissions (undesirable)	Environment Social

Despite many researchers being concerned about improving operational efficiency in the food industry, few studies integrate all three E, S, G categories into their analyses, some researchers have integrated environmental and social dimensions alongside economic factors, as shown in Table 2.

Egilmez et al. (2014) integrates the results of Economic Input-Output Life Cycle Assessment (EIO-LCA) analysis into the DEA model to create a life cycle-based frontier analysis, identifies which criteria significantly contributing to the supply chain performance of the food manufacturing in the US. Selected environmental categories include carbon footprint, water withdrawals, energy footprint, cropland, grazing land, forest land and fishery.

Zhang et al. (2021) applied the Entropy-DEA Model to evaluate world food production efficiency and sustainability, selecting the top 10 countries in agricultural production over the past few years as the 10 DMUs. In the input and output selection process, they considered both expected and unexpected factors to capture various aspects of environmental efficiency, specifically natural disposability and management disposability and the social factor which is labor force. The output indicators included agricultural GDP (expected) and CO2 emissions (unexpected), while the five input indicators were labor force, agricultural arable land area, agricultural irrigation area, agricultural machinery, and fertilizer consumption.

Vaez-Ghasemi et al. (2022) used DEA to evaluate the cost efficiency of sustainable supply chains in the food industry. They selected six input factors from the Environmental, Economic, and Social categories: raw materials, staff, water usage, inter-products, green products, and CO2 emissions to assess sustainability performance in the first stage.

In summary, most existing research emphasizes environmental and social dimensions, with limited integration of governance aspects alongside economic factors. This research expands the scope to include all three ESG dimensions, this could offer a more comprehensive evaluation of sustainability practices within the food industry in Taiwan, contributing to a deeper understanding of their impact on operational performance.

3. Methodology

The research proposes a conjunction use between Super-efficiency model SBM (Slacks-Based Model) and Malmquist productivity index to measure ESG operational performance. While Super-SBM evaluates efficiency, identifies benchmark and ranking of DMUs, the Malmquist Productivity Index (MPI) is commonly used to measure productivity change over time. There are also many studies utilizing this combination to conduct deeper research when measuring productivity of the DMUs over the past decade. (Liu et al., 2019; Liu, 2023; Sun et al., 2005; Long et al., 2020; Lan et al., 2022; Shah et al., 2022; Ganji & Rassafi, 2019)

Before applying Super-SBM model and Malmquist DEA, the data must be validated to ensure their suitability, all input and output variables must exhibit a positive correlation. The Pearson test will be conducted to verify this condition.

3.1 Using Pearson Test to Validate Data

Coefficient r between two variables x and y is given by:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad (1)$$

Where:

n is the sample size.

x_i and y_i are individual data points.

While $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$ represents the sample means and analogous for $\bar{y}$.

Interpretation:

Correlation coefficient r_{xy} refers closer to +1 suggests a strong positive relationship, closer to -1 indicates a strong negative relationship, closer to 0 implies weak linear relationship between the variables.

Rather than relying solely on correlation tests, DEA emphasizes two key principles: homogeneity and isotonicity. Homogeneity requires that all DMUs being evaluated operate under similar conditions. Isotonicity means that as inputs (resources) increase, outputs (production) should not decrease, reflecting a positive relationship between inputs and outputs.

A positive relationship indicates a good linear fit between inputs and outputs for DEA.

3.2 Super SBM Model

DEA model measures the performance of each Decision-Making Unit (DMU), compares DMUs against one another and evaluates their efficiency using linear programming instead. DEA model measures the efficiency of each Decision-Making Unit (DMU). The CCR DEA model is as follows:

$$\text{Max Efficiency } \theta = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \tag{2}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \;; \qquad j = 1, \dots, n,$$

$$v_r, v_i \geq 0 \;; \qquad r = 1, \dots, s \;; \qquad i = 1, \dots, m.$$

Where:

x_{ij}: amount of input i for DMU j

y_{rj}: amount of output r for DMU j

u_r: weight assigned to output r

v_i: weight assigned to input i

The constraints ensure that the ratio of output vs. input should not exceed 1 for every DMU. The objective is to obtain weights v_i and u_r that maximize the ratio of DMU_0, the DMU being evaluated. Due to the constraints, the optimal objective value θ is at most 1, representing the frontier that defines the production possibility boundary. This indicates that DEA calculates relative and not absolute efficiency scores.

The Super Slacks-Based Model (Super SBM) is an extension of the standard SBM model proposed by Tone (2001), which is a non-radial DEA model. Unlike radial models, the SBM model optimizes each input and output independently, allowing for non-proportional reductions in inputs or increases in outputs. This approach allows the model to account for slacks, or excess inputs and output shortfalls, individually for each resource and product associated with each DMU.

Given n DMUs with inputs and outputs matrices $X = (x_{ij}) \in R^{m\times n}$ and $Y = (y_{ij}) \in R^{s\times n}$, respectively. λ is a non-negative vector in R^n. The vector $s^- \in R^m$ and $s^+ \in R^s$ indicate the input excess and output shortfall, respectively.

The SBM efficiency score ρ for a specific DMU (0) is defined as:

$$\min \rho = \frac{1-\frac{1}{m} \sum_{i=1}^{m} s_i^- / x_{i0}}{1+\frac{1}{s} \sum_{i=1}^{s} s_r^+ / y_{r0}} \tag{3}$$

subject to
$$x_0 = X\lambda + s^-,$$
$$y_0 = Y\lambda - s^+,$$
$$\lambda \geq 0,\; s^- \geq 0,\; s^+ \geq 0\;,$$
$$0 < \rho \leq 1$$

Let an optimal solution for [SBM] be ρ^*; λ^*; s^{-*}; s^{+*}. Based on this optimal solution, we define a DMU as being SBM-efficient as follows:

A $DMU(x_0, y_0)$ is SBM-efficient, if $\rho^* = 1$. This condition is equivalent to $s^{-*} = 0$ and $s^{+*} = 0$, i.e., no input excesses and no output shortfalls in any optimal solution.

SBM ρ can be interpreted as ratio of mean input and output mix inefficiencies, the formula for ρ in (1) can be transformed into

$$\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{x_{i0}-s_i^-}{x_{i0}}}{\frac{1}{s}\sum_{r=1}^{s}\frac{y_{r0}+s_r^+}{y_{r0}}} \tag{4}$$

Where:

$(x_{i0} - s_i^-)/x_{i0}$ evaluates the relative reduction rate of input i

$(y_{r0} + s_r^+)/\ y_{r0}$ evaluates the relative proportional expansion rate of output r

If DMU A dominates DMU B so that $x_A \leq x_B$ and $y_A \geq y_B$, then $\rho_A^* \geq \rho_B^*$

3.3 Malmquist Productivity Index

The Malmquist productivity index (MPI) evaluates the performance of a DMU in two fixed periods.

Explanation of Terms:

TSE: Technical Efficiency score.

IEI: Input Efficiency Index.

OZ: Output levels or efficiency scores at different times and conditions.

CP: The Catch-Up effect, which assesses efficiency improvement.

FS: The Frontier Shift effect, which measures shifts in the production frontier.

The operational efficiency of the DMUs is measured from t to period t+1 as can be seen in equation:

$$CP^{t\to t+1} = \frac{OZ_{t+1}^{t+1}/OZ^{t+1}}{OZ_t^t/OZ^t} = \frac{TSE^{t+1}}{TSE^t} \tag{5}$$

$$FS_t^{t+1} = \left[\frac{\frac{OZ_t^t}{OZ^t} \times \frac{OZ_t^{t+1}}{OZ^{t+1}}}{\frac{OZ_{t+1}^t}{OZ^t} \times \frac{OZ_{t+1}^{t+1}}{OZ^{t+1}}}\right]^{0.5} = \left[\frac{TSE^t}{TSE^{t+1}} \times \frac{IEI^{t+1\to t}}{IEI^{t\to t+1}}\right]^{0.5} \tag{6}$$

Malmquist productivity index (MP_t^{t+1}) from period t to t+1 is measured as follows

$$MP_t^{t+1} = C^{t\to t+1} \times F_t^{t+1} = \frac{TSE^{t+1}}{TSE^t} \times \left[\frac{TSE^t}{TSE^{t+1}} \times \frac{IEI^{t+1\to t}}{IEI^{t\to t+1}}\right]^{0.5} \tag{7}$$

$$MP_t^{t+1} = \left[\frac{TSE^{t+1}}{TSE^t} \times \frac{IEI^{t+1\to t}}{IEI^{t\to t+1}}\right]^{0.5} \tag{8}$$

Where $MP_t^{t+1} > 1$ indicates that operational efficiency increased, $MP_t^{t+1} < 1$ indicates that operational efficiency decreased, and $MP_t^{t+1} = 1$ indicates that there has been no change in operational efficiency.

4. Results and Discussion

4.1 Collecting Data and Validating Test

In this study, Decision-Making Units (DMUs) refer to individual food companies in Taiwan.

To be included as a DMU, a company must meet the following criteria:

(1) Classification under the food industry sector refers to SASB (Sustainability Accounting Standards Board) for industry classification.

(2) Complete data for the period 2018-2023.

They are chosen based on data availability from sources such as the Taiwan Economic Journal (TEJ), Market Observation Post System (MOPS), and ESG reports. The final sample consists of 26 DMUs.

The selection of input and output is shown in Table 3.

Table 3: Input-output selection

Category	Code	Variable Description	Unit	Data source
Inputs	I1	Number of employees	people	MOPS (TWSE Market Observation Post System)
	I2	Employee benefits and wages	Thousand NTD	MOPS (TWSE Market Observation Post System)
	I3	Total operating cost	Thousand NTD	TEJ database
	I4	Total operating expense	Thousand NTD	TEJ database
Outputs	O1	Total operating revenue	Thousand NTD	TEJ database
	O2	Environment score		TEJ database
	O3	Social score		TEJ database
	O4	Governance score		TEJ database

I1-Number of employees: Chen & Zhu (2003); Katou & Budhwar (2015) stated that the number of employees is a critical input factor in the production function, directly influencing organizational productivity. An optimal number of employees ensures that workloads are balanced, allowing each employee to perform at their best (Gökşen, Pala, & Ünlü, 2019). Besides, firms need to reach an optimization point, balancing the number of employees and production outputs to maintain cost-effectiveness.

I2-Employee benefits and wages: employee benefits and wages can be seen as labor cost, since it reflects the value of labor relative to other inputs, which have a direct positive impact on work motivation and overall productivity (Kang et al., 2016; Primatami & Primadhita, 2020; Ray, 2004). This study uses the total employee benefits and wages, which include both salary payments and additional benefits, providing a comprehensive measure of a company's investment in its workforce.

I3-Total operating cost: includes cost of goods sold (COGS) and other direct production-related costs, such as raw material procurement, manufacturing processes, and logistics. Managing these costs by improving energy efficiency can reduce firms' operating costs resulting in enhancing both ESG performance and financial performance. Other research chose total cost of goods sold as an operational input for efficiency evaluation (Mao et al., 2022; Ondersteijn et al., 2006).

I4-Total operating expense: accounts for indirect costs that support daily business functions but are not directly tied to production. This includes administrative expenses, marketing costs, research & development (R&D) expenses, and facility maintenance. Some studies utilized operating expense as an input factor to evaluate performance (Bangarwa & Roy, 2022; Halkos & Tzeremes, 2012).

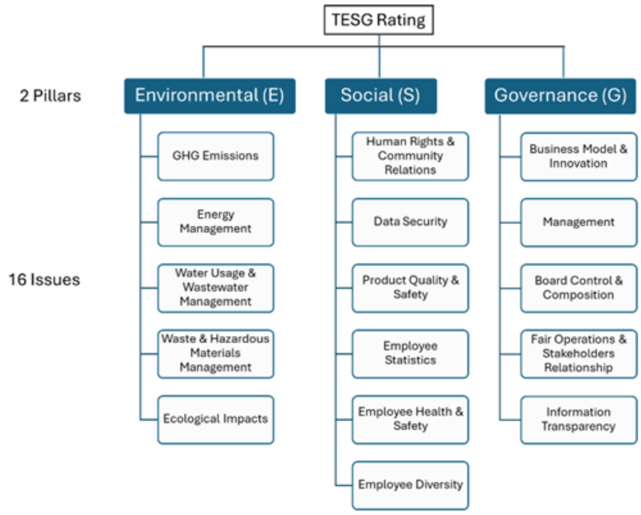

Figure 2: TESG Framework

Source: TEJ, 2022.

O1-Total operating revenue: The higher the operating revenue, the greater the sales volume contributes to the company's financial stability and market competitiveness. Chen & Zhu (2003) identified critical performance measures for DEA model, 92.59% of food companies indicated that revenue was the most important factor when evaluating productivity. Other studies selected operating revenue as an output factor in DEA model (Cook & Zhu, 2006; Malik et al., 2018; Pongpanich, Peng, & Wongchai, 2018; Wong & Wong, 2007).

O2-Environment score, O3-Social score, O4-Governance: ESG scores serve as outputs employing data from TESG, an ESG rating of Taiwan Economic Journal, whose framework is theory-based on international standards such as GRI Standards (developed by Global Reporting Initiative) for ESG performance evaluation (Figure 2) and SASB (Sustainability Accounting Standards Board) for industry classification. (TEJ, n.d.)

Pearson test helps identify relationships between input and output, this study tested correlations between inputs which are operational indicators and outputs including E, S, G scores and Operating revenue. The results are shown in Table 4.

Table 4: Input-output Correlations Test Result

		O1-Total Operating Revenue	**O2-Environment Score**	**O3-Social Score**	**O4-Governance Score**
I1-Number of employees	Pearson Correlation	0.851**	0.429**	0.336**	0.186*
	Sig. (2-tailed)	0.000	0.000	0.000	0.020
I2-Total Employee Wages and Benefits	Pearson Correlation	0.954**	0.421**	0.374**	0.125
	Sig. (2-tailed)	0.000	0.000	0.000	0.120
I3-Total operating cost	Pearson Correlation	0.998**	0.362**	0.359**	0.033
	Sig. (2-tailed)	0.000	0.000	0.000	0.684
I4-Total operating expense	Pearson Correlation	0.990**	0.345**	0.344**	0.029
	Sig. (2-tailed)	0.000	0.000	0.000	0.720

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

For the two other outputs, O2 (Environment score) and O3 (Social score), the input variables exhibit positive correlations at a moderate to weak level, ranging from 0.336 to 0.439, yet remain at a strong significance level at $p<0.01$. This indicates that these 4 operational inputs also contribute to ESG scores within the selected firms.

Although the Pearson correlation results indicate that the relationship between input factors and O4 (Governance Score) is weaker compared to other ESG outputs (ranging from 0.029 to 0.186), only I1 correlation is statistically significant at 0.05 p-value level; for other inputs I3 and I4, correlations and the p-values are relatively high (0.684 and 0.720 respectively), but they remain positive, which can be considered as a sign of not degrading the output O4.

While Pearson correlation test captures linear relationships, governance-related impacts often manifest through nonlinear dynamics, governance practices lead to development over time with incremental changes followed by later economic efficiency (Duit & Galaz, 2008). This highlights that these complex interactions and lagged effects cannot be fully captured by the correlation test. Moreover, governance dimension plays a core component of ESG performance, excluding O4 could lead to an incomplete assessment of ESG efficiency. Therefore, despite its weak statistical correlation with inputs, O4 Governance Score is included as an output in this study, aligning with prior literature emphasizing its importance in corporate sustainability and performance evaluation.

4.2 Super-SBM Model Results

Note: Throughout the following sections, the DMUs code represents the four-digit company code listed on the Taiwan Stock Exchange (TWSE).

In the study, the panel data was collected from 26 DMUs, using 4 input and 4 output variables over the period from 2018 to 2023. To align with the structure of the Super-SBM model—which works by analyzing a set of inputs and outputs of DMUs without accounting for time-series fluctuations—it was necessary to simplify the dataset. Therefore, the panel data was averaged across years for each firm to maintain a balanced demonstration of long-term operational and ESG performance.

Using yearly data would significantly increase the number of DMUs (e.g., 26 companies x 6 years = 156 DMUs), which could complicate the interpretation of efficiency rankings. Moreover, the focus of this study is to evaluate firms' general efficiency performance over time, rather than short-term fluctuations. Averaging data helps to neutralize the outcomes caused by external shocks—such as Covid-19 or political conflict—as well as provide a stable and representative input for Super-SBM analysis, keeping the model practical and interpretable.

The results presented in Table 5 indicate that DMU 13 achieved the highest Super-SBM score of 21.822, followed closely by DMU 17 with a score of 20.167. These two companies significantly outperform the rest, with a notable gap before DMU 9, which ranks third with a score of 10.228. At the lower end of the range, DMUs 8, 7, and 10, which all score below 1, recorded the weakest performance, reflecting substantial inefficiencies.

Table 5: Results of the ranking using Super-SBM model

DMUs	DMUs code	Score	Super-SBM Rank
13	1229	21.822	1
17	1234	20.167	2
9	1219	10.228	3
1	1201	7.376	4
22	1737	4.573	5
24	3054	3.931	6
15	1232	3.688	7
23	1796	3.613	8
14	1231	3.036	9
18	1235	2.676	10
21	1702	2.633	11
16	1233	2.627	12

26	4207	2.428	13
5	1215	2.138	14
3	1210	1.678	15
19	1236	1.618	16
11	1225	1.613	17
4	1213	1.175	18
25	4205	1.117	19
12	1227	1.056	20
20	1264	1.032	21
2	1203	1.021	22
6	1216	1	23
10	1220	0.881	24
7	1217	0.83	25
8	1218	0.549	26
Average		4.019	
Max		21.822	
Min		0.549	
Standard Deviation		5.449	

The slacks analysis in Table 6 reveals that many DMUs exhibit noticeable inefficiency in both input and output usage. This suggests that companies utilize more resources than necessary to achieve their current levels of output, or that with their existing inputs, they still have the potential to reach higher performance levels. The higher-ranking DMUs (DMU 13, DMU 17 and DMU 1) show larger slacks in operating statistics compared to the lower-ranking DMUs, emphasizing that even leading firms are not operating perfectly efficiently. Instead, they outperform primarily because of superior output achievements rather than optimal resource utilization.

Table 6: Results of the Super-SBM model with slacks

DMUs	DMUs code	Rank	(I)Number of employees	(I)Total Employee Wages and Benefits	(I)Total operating cost	(I)Total operating expense	(O)Total operating revenue	(O)Environ -ment Score	(O)Social Score	(O)Govern -ance Score
13	1229	1	1648.766	5898462.456	134291515.9	56364050.17	202158021.8	0	0	10.04
17	1234	2	2825.374	7551890.549	184406719.8	74255628.4	274718138.1	0	3.845	10.053
9	1219	3	1153.795	3003487.201	59539909.31	27848854.43	93423734.61	0	0	0
1	1201	4	1331.57	4979137.705	154899848.1	60477192.64	229818525.9	0	7.278	0
22	1737	5	946.848	1264361.888	12060593.16	4450205.73	16571250.64	27.904	0	0
24	3054	6	42.415	34995.573	1041403.583	34029.757	1223461.739	0	1.36	4.554
15	1232	7	874.687	1106605.12	0	2273964.328	1624385.792	0	0	0
23	1796	8	148.293	459314.104	1275546.593	498453.524	2017245.753	3.479	0	0
14	1231	9	0	616088.69	23129514.23	6012879.762	30843169.4	0.45	6.474	0
18	1235	10	5.833	39221.833	77708.333	45743.5	55836	10.238	2.23	2.25
21	1702	11	217.377	518109.119	8543321.313	0	8815440.974	3.75	2.136	0
16	1233	12	0	859392.066	4849573.227	249317.388	5669510.094	0.876	0.697	0
26	4207	13	283.953	392184.3	5393097.002	392162.501	6165472.803	0	1.8	0
5	1215	14	94.79	0	26515138.56	5721899.158	32928860.96	1.525	0	0
3	1210	15	0	1351259.132	0	19465057.75	23032209.81	9.207	2.807	4.601
19	1236	16	0	42933.225	2052278.663	473676.294	2800561.673	0	12.221	2.435
11	1225	17	332.982	236415.282	0	239064.737	936819.253	1.379	0	10.939
4	1213	18	1.752	41833.63	0	17407.671	126707.464	0	6.983	0
25	4205	19	54.541	0	275822.879	0	0	0	0	12.911
12	1227	20	181.677	0	995069.097	0	0	0	4.159	1.234
20	1264	21	0	0	392094.148	0	0	0	20.546	0
2	1203	22	0	0	349884.672	0	0	0	0	0
6	1216	23	0	0	0	0	0	0	0	0
10	1220	24	48.547	25775.764	0	40461.48	0	0	12.006	0
7	1217	25	182.218	108530.153	0	306186.328	0	0	0	2.288
8	1218	26	384.518	643947.655	0	605922.145	0	0	2.843	1.446

In summary, Super-SBM model results reveal that there is a huge gap between top-ranking DMUs and bottom-ranking DMUs, highlight that Taiwan's food industry still has significant room for operational and sustainability improvements. Furthermore, the slacks analysis points out that while the upper ranking DMUs outperform other DMUs in the scale, they tend to overuse input resources and fall short in fully maximizing output efficiency. On the other hand, to catch up with other DMUs in the industry, the lower-ranking DMUs need to execute more dynamic transformations such as investing in innovation, upgrading management systems and improving ESG integration, therefore enhancing their positions within the industry.

4.3 Malmquilst Productivity IndexResults

Catch-up Effect (Efficiency Change)

As shown in Table 7, the Catch-up effect determines how much DMUs change in relative efficiency year over year, spanning from 2018 to 2023. A Catch-up score greater than 1 indicates progress toward the efficiency frontier, while a score equal to 1 suggests no change, and a score less than 1 reflects a decline in efficiency. The overall Catch-up average is 1.1692, revealing that, in general, Taiwan's food industry improved its efficiency from 2018 to 2023. DMU 13 recorded the highest average score of 2.5064, showing significant efficiency improvement, though it experienced a sharp decline in 2021–2022 with a Catch-up score of only 0.0890. In contrast, DMU 11 posted the lowest average Catch-up score at 0.8298, indicating consistent regression, with its worst performance at the beginning of the period (2018–2019), scoring just 0.1235.

DMU 6 and DMU 22's catch-up indices remain stable at 1 in 6 consecutive years, and the same with DMU 1 in 4 consecutive years from 2019 to 2022. Meanwhile, DMU 4 and DMU 16 show high variability year to year, reflecting inconsistency or external shocks.

Table 7: Annual efficiency changes in Catch-up effect from 2018 to 2023

DMUs	DMUs code	2018=>2019	2019=>2020	2020=>2021	2021=>2022	2022=>2023	Average
1	1201	1.4589	1.0000	1.0000	1.0000	1.0000	1.0918
2	1203	0.9645	1.0152	0.9959	0.9903	1.0067	0.9945
3	1210	1.0307	1.0233	1.0785	1.0685	0.9612	1.0324
4	1213	0.4035	0.6095	1.4735	1.2304	1.1710	0.9776
5	1215	1.0153	0.9785	1.8756	0.9119	1.0043	1.1571
6	1216	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
7	1217	0.8672	1.1510	1.0130	1.1995	0.5232	0.9508
8	1218	0.9635	0.8096	0.9394	0.9119	1.3782	1.0005
9	1219	3.7559	1.1475	1.6447	0.0973	1.0000	1.5291
10	1220	1.1601	1.0669	0.8031	0.6761	1.5791	1.0571
11	1225	0.1235	1.1217	0.8308	0.7921	1.2808	0.8298
12	1227	1.0095	0.9887	0.9946	0.7086	0.9931	0.9389
13	1229	1.1435	9.5530	0.7816	0.0890	0.9648	2.5064
14	1231	0.9942	0.9965	1.9494	0.9811	1.0256	1.1894
15	1232	3.4583	1.1158	0.8959	0.6881	0.9111	1.4139
16	1233	0.3569	2.0734	0.6644	0.7591	1.3636	1.0435
17	1234	1.0000	2.9493	0.4197	0.8079	1.1110	1.2576
18	1235	1.1251	1.1218	0.5114	2.1961	0.5195	1.0948
19	1236	2.3345	0.4138	0.9368	0.9581	1.4608	1.2208
20	1264	0.8937	0.8601	1.0243	1.0057	1.1955	0.9958
21	1702	1.0122	0.9118	0.9191	0.9924	2.2747	1.2220
22	1737	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
23	1796	0.9178	1.0911	0.9944	0.2787	3.7751	1.4114
24	3054	1.0070	0.7279	3.1261	0.4617	1.4863	1.3618
25	4205	0.9255	1.0191	1.2898	0.8624	0.8488	0.9891
26	4207	1.2725	1.0444	1.5374	0.2664	1.5396	1.1321
	Average	1.1998	1.4150	1.1423	0.8436	1.2452	1.1692
	Max	3.7559	9.5530	3.1261	2.1961	3.7751	2.5064
	Min	0.1235	0.4138	0.4197	0.0890	0.5195	0.8298
	SD	0.8077	1.7247	0.5481	0.4170	0.6250	0.3211

Frontier-shift Effect (Technology)

Besides catch-up effect, the frontier-shift effect also must be considered, as catch-up effect is calculated by measuring the distances from the respective frontiers. The frontier-shift effect, which is also known as technology change, reflects how the best-practice production frontier itself moves over time. A Frontier-shift score greater than 1 implies the frontier has advanced, while a score equal to 1 shows no change, and a score below 1 implies regression.

Table 8 demonstrates the changes in frontier-shift effect among DMUs.

The average frontier-shift score across all DMUs is 1.2040, showing a general upward shift in the industry's best-practice frontier, meaning Taiwan’s food industry top performers continuously improved their technological or structural advancement.

Industry leaders such as DMU 13 and DMU 9, with both high catch-up and high frontier-shift scores, are not only having high catch-up efficiency but are also likely contributing to technological innovation that shifts the frontier. DMU 9 has the highest average score at 2.9521, especially during the period of 2019 to 2022, when its annual scores consistently ranged from 2.4321 to 5.6465.

Table 8: Annual efficiency changes in Frontier-shift effect from 2018 to 2023

DMUs	DMUs code	2018=>2019	2019=>2020	2020=>2021	2021=>2022	2022=>2023	Average
1	1201	0.9949	1.1162	1.0000	0.9623	0.9916	1.0130
2	1203	0.9645	1.0592	1.0052	0.9529	1.1214	1.0207
3	1210	1.0761	1.0228	1.0281	1.0950	1.0066	1.0457
4	1213	1.0614	0.9214	0.9416	1.3216	0.7160	0.9924
5	1215	1.3158	1.7201	0.7733	1.0292	1.0019	1.1681
6	1216	0.9934	1.0000	1.0000	1.0000	1.0000	0.9987
7	1217	1.1203	1.0836	1.0066	0.9309	0.9681	1.0219
8	1218	1.1982	1.1806	0.9611	0.9590	0.9264	1.0451
9	1219	0.5259	5.6465	2.4321	5.2248	0.9312	2.9521
10	1220	0.7572	1.2130	1.3016	1.1572	0.9498	1.0758
11	1225	1.5649	0.7219	0.9427	0.9535	0.8807	1.0128
12	1227	1.0580	1.0065	0.9986	1.0100	1.2383	1.0623
13	1229	2.8557	0.7904	0.8128	3.3593	1.0120	1.7660
14	1231	1.0263	1.0551	1.0089	1.1747	0.9774	1.0485
15	1232	0.3377	0.9022	1.0400	1.0209	1.2320	0.9066
16	1233	1.2833	0.9877	1.0033	0.9520	1.1259	1.0705
17	1234	1.0000	0.1756	2.9544	2.8763	0.8410	1.5694
18	1235	1.3847	0.7439	1.1121	1.4663	0.9873	1.1389
19	1236	0.9907	2.0275	0.8158	0.7532	1.3666	1.1908
20	1264	0.9492	1.0761	0.9186	0.9923	0.9729	0.9818
21	1702	1.2544	1.0336	0.9825	0.9968	0.6522	0.9839
22	1737	1.0102	1.0000	0.9722	1.0263	1.0191	1.0056
23	1796	0.9665	1.3496	1.0552	1.2334	0.6221	1.0453
24	3054	1.0958	0.9255	0.7572	0.6426	1.7237	1.0290
25	4205	1.0074	1.1469	0.9743	0.9380	0.9737	1.0080
26	4207	1.1638	4.0432	1.3049	3.7253	0.5173	2.1509
	Average	1.1137	1.3442	1.1194	1.4521	0.9906	1.2040
	Max	2.8557	5.6465	2.9544	5.2248	1.7237	2.9521
	Min	0.3377	0.1756	0.7572	0.6426	0.5173	0.9066
	SD	0.4313	1.1043	0.4857	1.0899	0.2392	0.4509

In contrast, some DMUs exhibit high frontier-shift scores but low catch-up scores. For instance, DMU 26 posted a strong average frontier-shift score of 2.1509 across 2018–2022, indicating the DMU helped push the frontier forward but it wasn't catching up as fast itself (catch-up score at 1.1321). This may imply that the DMU is innovating the frontier but not fully capitalizing on it internally.

DMUs with low catch-up and low frontier-shift score (DMU 4 and DMU 20), indicating poor relative efficiency improvement and little contribution to industry innovation. On the other hand, DMU 15 with high catch-up (1.4139) but low frontier-shift scores (0.9066), proving that this DMU is doing well in internal efficiency improvements but may rely on existing technologies rather than pioneering new ones.

4.3.3 Malmquilst Productivity Index

Malmquilst Productivity Index (MPI) is computed as the product of Catch-up and Frontier-shift. MPI greater than 1 indicates progress in the total factor productivity of the DMUs over the period, while MPI equals 1 indicates no change and MPI less than 1 indicates decay in the total factor productivity.

$$MPI = (Catch - up) \times (Frontier - shift)$$

As shown in Table 9, the analysis for Taiwanese food industry companies from 2018 to 2023 reveals significant trends influenced by key external events and environmental, social, and governance (ESG) factors. The average MPI strongly fluctuates, indicating that the food industry DMUs experienced many external shocks as well as internal adaptability.

Table 9: Annual changes in Malmquilst Productivity Index from 2018 to 2023

DMUs	DMUs code	2018=>2019	2019=>2020	2020=>2021	2021=>2022	2022=>2023	Average
1	1201	1.4515	1.1162	1.0000	0.9623	0.9916	1.1043
2	1203	0.9303	1.0753	1.0011	0.9437	1.1289	1.0159
3	1210	1.1091	1.0466	1.1088	1.1700	0.9675	1.0804
4	1213	0.4282	0.5616	1.3874	1.6261	0.8384	0.9683
5	1215	1.3360	1.6832	1.4503	0.9386	1.0062	1.2829
6	1216	0.9934	1.0000	1.0000	1.0000	1.0000	0.9987
7	1217	0.9715	1.2473	1.0197	1.1166	0.5065	0.9723
8	1218	1.1544	0.9559	0.9028	0.8745	1.2768	1.0329
9	1219	1.9751	6.4792	4.0000	0.5086	0.9312	2.7788
10	1220	0.8785	1.2941	1.0453	0.7824	1.4998	1.1000
11	1225	0.1933	0.8097	0.7832	0.7553	1.1280	0.7339
12	1227	1.0680	0.9952	0.9931	0.7157	1.2298	1.0004
13	1229	3.2654	7.5510	0.6353	0.2990	0.9764	2.5454
14	1231	1.0204	1.0514	1.9668	1.1525	1.0024	1.2387
15	1232	1.1679	1.0067	0.9317	0.7025	1.1225	0.9863
16	1233	0.4580	2.0480	0.6666	0.7227	1.5353	1.0861
17	1234	1.0000	0.5179	1.2399	2.3237	0.9343	1.2032
18	1235	1.5580	0.8345	0.5687	3.2202	0.5129	1.3389
19	1236	2.3128	0.8390	0.7642	0.7217	1.9963	1.3268
20	1264	0.8482	0.9256	0.9410	0.9979	1.1631	0.9751
21	1702	1.2696	0.9424	0.9030	0.9892	1.4835	1.1175
22	1737	1.0102	1.0000	0.9722	1.0263	1.0191	1.0056
23	1796	0.8871	1.4725	1.0493	0.3437	2.3484	1.2202
24	3054	1.1035	0.6737	2.3672	0.2967	2.5620	1.4006
25	4205	0.9323	1.1688	1.2566	0.8090	0.8265	0.9986
26	4207	1.4809	4.2225	2.0062	0.9924	0.7964	1.8997
	Average	1.1847	1.6353	1.2293	0.9997	1.1840	1.2466
	Max	3.2654	7.5510	4.0000	3.2202	2.5620	2.7788
	Min	0.1933	0.5179	0.5687	0.2967	0.5065	0.7339
	SD	0.6087	1.7372	0.7072	0.6096	0.4872	0.4696

Notably, 2020 marks the first phase of COVID-19 pandemic, MPI peaked at 7.5510 and reached its lowest at 0.5179 during 2019–2020, reflecting extreme divergence in productivity performance among firms. This suggests that while some firms adapted swiftly, others were severely disrupted by international logistics delays, raw material and labor shortages, and consumer uncertainty. COVID-19 continued affecting the industry more severely in 2021, witnessing a decline in productivity across most firms, with the average MPI falling to 1.2293 and many DMUs—such as DMU 13 (from 7.5510 to 0.6353), DMU 18 (0.5687), DMU 16 (0.6666)—recording drops. In operating terms, the analysis clearly shows that packaged and convenience food producers and retail-oriented companies were the least affected or even benefited from the COVID-19 pandemic due to changing consumers' habits. In contrast, fresh and perishable goods producers and specialty food companies faced the most challenges. Beverage producers experienced mixed outcomes, depending on their ability to shift to retail channels. During the COVID-19 pandemic, companies faced many challenges in integrating ESG practices such as higher food waste, increased packing waste, and delays in sustainability projects. In the social dimension, COVID-19 raised many concerns in food factories about worker health and safety, labor shortages, and stress on workers. In the governance dimension, weak planning or risk management firms faced challenges in responding to crises and gaining stakeholders' trust.

2022 witnesses the lowest average MPI below 1, the highest score at 3.2202 and lowest score at 0.2967, indicating overall regression of the industry. This likely reflects the combined pressure of post-COVID recovery fatigue and the economic fallout from the Russia–Ukraine war. DMUs such as DMU 13, 23 and 24 saw MPI fall below 0.4, indicating sharp productivity regressions, MPI of most of the rest of DMUs during this year also decrease to under 1.

The Russia-Ukraine war that started in 2022 caused a significant disruption in global supply chains, leading to a critical shortage of raw materials and skyrocketing prices especially in commodity and energy, which triggered global inflation. This situation led to many challenges that food companies need to confront within environment sector, such as increased carbon footprint, energy costs and emissions. Balancing operational costs while keeping prices affordable became a formidable task. Furthermore, the crisis revealed governance challenges within some Taiwanese food companies, investor pressure increased, raising questions about how companies could sustain sustainable sourcing amid global conflicts.

By 2022 to 2023, the average MPI showed a moderate recovery, rising to 1.1840. This improvement can be linked to companies' strategic adjustments in response to earlier challenges, such as investing in ESG compliance, adopting automation, optimizing supply chain management. Additionally, some firms may have benefited from clearer regulations, like the Taiwan ESG reporting guidelines, which became more prominent during this period. Companies that had previously invested in innovation and structural changes—such as DMU 9, 13—likely began to see the positive effects of those efforts, leading to improved efficiency and progress toward the industry frontier.

To sum up, MPI analysis describes a fluctuated trend over the research period, which witnessed some severe external shocks including COVID-19 and Ukraine-Russia war. Despite these challenges, Taiwan's food companies demonstrated remarkable resilience and managed to recover significantly. Moreover, the development of Taiwan's ESG regulations has provided a solid foundation for the industry's sustainable growth, contributing to its long-term stability.

5. Conclusions and Suggestions

5.1 Conclusions

The primary goal of this study was to measure the efficiency of operational performance and ESG practices of Taiwan's food processing companies. With the increasing focus on sustainable development and environmental responsibility, it is crucial to understand how integrating ESG principles affects the efficiency of firms in the food sector. This research aimed to fill the gap in the existing literature by applying DEA model to evaluate how operational productivity influences ESG performance. This study identifies industry leaders and laggards within the sector, providing practical insights for companies to enhance their operational efficiency while maintaining strong ESG commitments. offers insights into how sustainability initiatives can drive improvements in both operational efficiency and ESG outcomes.

To achieve these objectives, the study employed the Super-SBM (Slack-Based Measure) model to assess the relative efficiency of selected DMUs and the Malmquist Productivity Index (MPI) to track changes in productivity over the period from 2018 to 2023. Data on inputs, including the number of employees, employee wages and benefits, total operating cost, and total operating expense, were collected alongside outputs including total operating revenue and ESG scores (environmental, social, and governance dimensions). Prior to model application, a Pearson correlation test was conducted to ensure a positive relationship between inputs and outputs.

The Super-SBM model results reveal a significant gap between top-ranking and bottom-ranking DMUs, indicating that Taiwan's food industry has considerable potential for efficiency improvement. While higher-ranking DMUs outperform others, they often overuse input resources and fail to maximize output efficiency. In contrast, lower-ranking DMUs need to implement dynamic changes—such as innovation, management upgrades, and better ESG integration—to enhance their operational performance and industry standing.

The MPI results reflected a fluctuating trend throughout the research period, significantly influenced by external factors such as the COVID-19 pandemic and the Russia–Ukraine war. The analysis also indicated a general upward shift in the efficiency frontier, suggesting that industry leaders continued to innovate and optimize processes. However, the disparity between high-ranking and low-ranking DMUs highlights the need for consistent improvement across the sector.

This study contributes to the academic discourse by integrating ESG performance into operational efficiency evaluation within the food industry context. The application of Super-SBM and MPI offers a thorough understanding of both cross-sectional efficiency and intertemporal productivity changes. Practically, the findings provide food companies with strategic insights to enhance both operational efficiency and ESG integration, helping them stay competitive while complying to sustainability regulations.

5.2 Suggestions

There are several potential directions for future research.

1. One important area is addressing the limitation posed by using averaged panel data in the Super-SBM model. While averaging data over multiple years helps simplify the model and capture long-term performance trends, it inevitably masks short-term variations and hinders a detailed analysis of how efficiency shifts in response to external events. To overcome this limitation, future studies could consider using a dynamic DEA model or conducting year-to-year efficiency assessments to capture how companies respond to sudden changes, such as economic disruptions or regulatory updates.
2. A comparative study across different industries could also help identify sector-specific challenges and best practices in ESG integration. Examining how various industries implement sustainability initiatives and manage operational efficiency would provide valuable insights into cross-industry differences and shared obstacles.
3. Additionally, conducting a longitudinal study spanning several decades would enable researchers to explore how long-term regulatory changes and evolving ESG standards impact operational performance. Analyzing data over an extended period would help distinguish temporary fluctuations from sustained efficiency improvements, offering insights into the long-term effectiveness of sustainability initiatives.

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