THE IMPACT OF ESG ON THE FINANCIAL EFFICIENCY OF FOOD COMPANIES

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ABSTRACT

Given the growing importance of organizations' environmental, social, and governance (ESG) performance, this paper estimates efficiency and examine ESG influence the food companies for the period of 2019-2024. The study has applied a DEA-Malmquist total factor productivity (TFP) index and its components to assess the technical efficiency and technological change of 21 food companies, including 5 companies with ESG reports. The result indicates that not all companies with ESG reporting have high TFP. The public ESG report has been a voluntary practice by companies, which means there has been no tight auditory obligation to it. The reports have been made public under the company names, so there has been little possibility of falsification, but it has still been possible for companies to modify inadequate or irrelevant actions to appear green. Therefore, government intervention or guarantees for companies, such as a green certification, are required to supplement ESG reports and make them to improve financial efficiency.

Keywords: Performance, technical efficiency, Data envelopment analysis, Malmquist index.

1. INTRODUCTION

In recent years, the problems of environmental pollution and climate change have become increasingly serious. Therefore, many countries around the world have agreed on the importance and urgency of sustainable development to solve this problem. ESG stands for Environmental, Social, and Governance, an important set of criteria to assess the level of sustainability and responsibility of a business in its business activities. In which, the "Environment" factor (E) focuses on reducing pollution, protecting natural resources and minimizing the impact of climate change. ESG (Environmental - Social - Governance) report is a document that synthesizes information about a business's operations according to ESG criteria. ESG reporting has important impacts on businesses, investors and the State. The agrifood sector holds a unique role in the global transition to sustainable development [1], as it has significant environmental and social impacts along its supply chains [2-4]. To demonstrate how corporates address these various challenges in their own operations and along their supply chains, the disclosure of environmental, social and governance (ESG) information has become an increasingly common practice by corporates, also in the agrifood sector [5].

The intense competition within the food industry underscores the necessity of evaluating the operational efficiency of food companies. Such assessments are critical not only for corporate managers but also for investors who seek high returns. Among various available methodologies for measuring firm efficiency, Data Envelopment Analysis (DEA) has gained widespread recognition as a powerful and flexible non-parametric methodology for performance evaluation. As highlighted by [6], DEA enables the relative assessment of the efficiency of individual decision-making units (DMUs) by comparing them within a defined peer group operating under similar conditions. This approach is particularly effective in application domains where multiple inputs are utilized to produce multiple outputs, allowing for a comprehensive evaluation of each unit's operational performance in relation to the best-performing entities within the same environment.

The food companies with strong ESG strategies often attract investment and are highly valued in the market, which promotes growth and stability of stocks and brand value, creating a competitive advantage in the financial market. Therefore, it can be said that ESG plays an important role as an indicator, helping stakeholders understand how food companies manage risks and take advantage of opportunities in all three aspects of environment, society and governance. Therefore, this study examines the business efficiency of **21 food companies listed on the Ho Chi Minh City Stock Exchange,** with the objective of identifying the most efficient firms and assessing whether those firms have published **Environmental, Social, and Governance (ESG)** reports. In this study, the DEA-Malmquist Total Factor Productivity (TFP) index has been employed as the analytical framework to assess changes in productivity over time. This method is particularly well-suited for panel data analysis, as it facilitates the tracking of performance dynamics across multiple time periods. As recommended by [7], the DEA-Malmquist index not only quantifies the overall shift in productivity but also allows for a detailed decomposition of this change into two key components: technical change, which reflects shifts in the production frontier due to innovation or technological progress; and technical efficiency change, which captures variations in a decision-making unit’s ability to utilize existing resources effectively relative to the frontier.

2. LITERATURE REVIEW

ESG refers to a set of criteria used to evaluate a firm's performance in relation to environmental**,** social, and governance dimensions of sustainable development**.** The ESG framework comprises three core dimensions, each addressing distinct aspects of a firm’s sustainability performance: E – Environmental: This category encompasses standards related to environmental protection and natural resource management, including the impacts of climate change and carbon emissions, water use and pollution control, and resource extraction such as deforestation; S – Social: This dimension addresses social issues ranging from basic concerns like customer satisfaction to broader themes such as diversity, equity, and inclusion (DEI), privacy and data security, and community engagement; G – Governance: This set of standards pertains to internal organizational practices, with a focus on corporate governance, board structure, and the protection of intellectual property rights, among others.

Efficiency frontier analysis is typically categorized into parametric and non-parametric approaches. The parametric method focuses on estimating production or cost functions for companies, with the resulting regression-based functions treated as optimal benchmarks [8]. Moreover, this method requires a relatively large sample size. In contrast, the non-parametric approach**,** specifically Data Envelopment Analysis (DEA)**,** utilizes the entire dataset collected from financial institutions to estimate a sample-wide efficient frontier, against which the performance of each institution is evaluated by comparing its current position to the optimal benchmark. This approach is therefore considered more flexible than parametric methods [9-11] and is particularly well-suited for evaluating non-productive institutions**.** Data Envelopment Analysis (DEA) has become a widely adopted and valuable tool for assessing the efficiency of entities that utilize multiple inputs to produce multiple outputs, especially in contexts where the underlying production relationships are complex or difficult to specify.

DEA is defined as "a mathematical programming methodology that can be applied to assess the relative efficiency of a variety of institutions using a variety of input and output data" [12]. Avkiran [13] also defines DEA as "an efficient frontier technique that computes a comparative ratio of weighted outputs to weighted inputs for each decision-making unit (DMU) using linear programming". The conceptual foundation of the efficiency frontier, often referred to as the enveloping curve, can be traced back to the seminal work of [9], who laid the groundwork for modern efficiency analysis. In his study, a production frontier model was introduced that incorporated multiple inputs and a single output, aiming to assess the production efficiency of decision-making units (DMUs). This approach focused on evaluating both technical efficiency—reflecting the ability of a DMU to obtain maximum output from a given set of inputs—and allocative efficiency, which considers the cost-effectiveness of input combinations under the assumption of constant returns to scale (CRS). Building upon this foundation, the development of Data Envelopment Analysis (DEA) was formally introduced and structured by [10], who extended Farrell's initial framework to accommodate multiple inputs and multiple outputs. Their model synthesized these elements into a comprehensive scalar efficiency score, facilitating the comparative evaluation of DMUs under the CRS assumption. Subsequently, Banker et al. [14] advanced this methodology by generalizing the CRS model to a variable returns to scale (VRS) setting, thereby enabling a more detailed decomposition of technical efficiency into two distinct components: pure technical efficiency, which captures managerial performance, and scale efficiency, which reflects the impact of operational size on productivity. These advancements marked significant milestones in the evolution of efficiency analysis, establishing DEA as a robust tool in empirical performance evaluation.This study adopts the Data Envelopment Analysis (DEA) methodology due to its strong theoretical foundation and widespread empirical validation across various fields. As emphasized by [15], one of the key advantages of DEA lies in its non-parametric nature, which eliminates the need to specify a predefined functional form for the production technology.

In other words, DEA does not require prior assumptions about the mathematical relationship between inputs and outputs, nor does it necessitate predefined weights for aggregating these factors. This feature enhances its flexibility and makes it particularly suitable for evaluating the relative efficiency of decision-making units (DMUs) operating in complex or heterogeneous environments. Furthermore, as noted by [16, 17], DEA provides a more nuanced and holistic assessment of performance compared to conventional productivity ratios typically employed in financial analysis. Unlike simple financial indicators, which often focus on partial aspects of performance, DEA integrates multiple inputs and outputs simultaneously, offering a more robust and comprehensive measure of operational efficiency. This methodological strength makes DEA a compelling choice for analyzing productivity in multifaceted organizational contexts.

When examining time-series analyses, most scholars tend to conceptualize efficiency in terms of total factor productivity (TFP) and employ the distance function framework [18] to measure changes in productivity (or efficiency) over time. Caves et al. [19] applied productivity indices derived from Shephard's distance function to develop a theoretical framework for measuring productivity and its changes, which subsequently evolved into the Malmquist productivity index approach. The Malmquist index enables the comparison of efficiency across different time periods.

Kim et al. [20] identified assets, cost of sales, and selling, general, and administrative expenses (SG&A) as key input variables for their DEA analysis. SG&A encompasses items such as salaries, employee benefits, and advertising expenditures. Both cost of sales and SG&A represent core components of operating expenses and are thus considered critical targets for optimization. In this context, assets and total operating costs - comprising cost of sales and SG&A - were employed as input variables, consistent with prior DEA studies in the field [21-23]. Similar input selections, including assets and operating costs, have also been adopted in DEA applications across other sectors [24-25]. For output variables, Kim et al. [20] selected sales and operating income. Sales, as a direct and intuitive indicator of business performance, have been widely used in DEA research to represent output [24]. Operating income - calculated as sales minus cost of sales and SG&A captures the firm's ability to efficiently manage inputs such as fuel and labor. Accordingly, it serves as a robust proxy for measuring operational efficiency and has been similarly applied in previous DEA studies. Therefore, in this study, the author approaches from the perspective of revenue and cost, so the author chooses three input variables as assets (X1), operating costs (X2), SG&A (X3) and two output variables as sales (Y1) and operating income (Y2).

3. METHODOLOGY

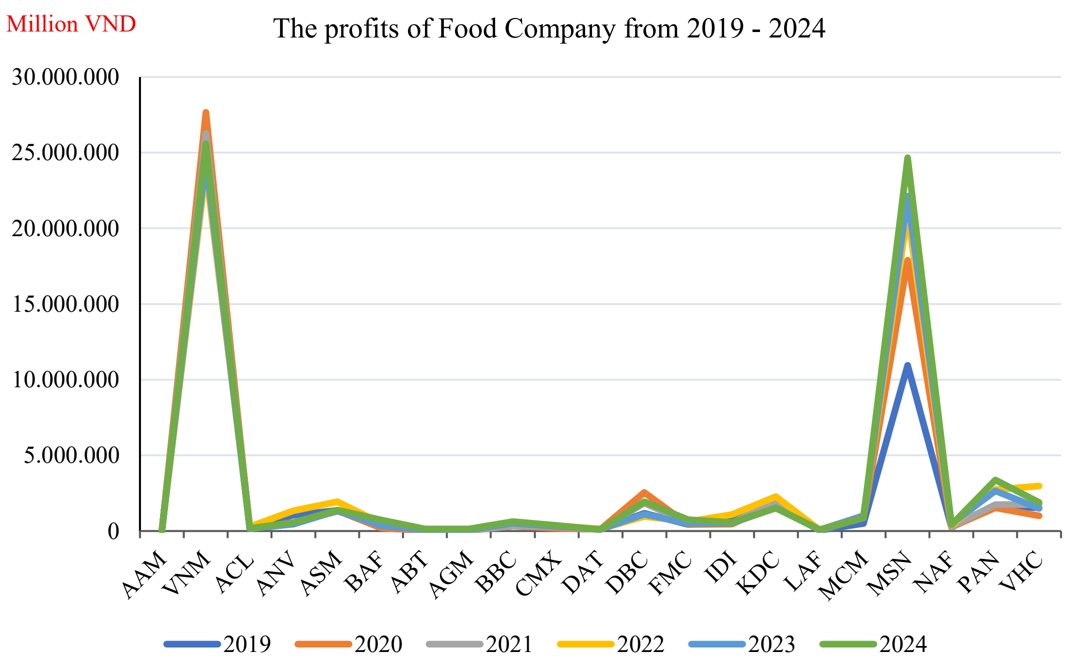
This study applies the DEA methodology to evaluate the operational efficiency of 21 food companies during the period 2019–2024 (Table 1) and the Profit of Food Company shown in figure 1, focusing on assessments of technical efficiency and the Malmquist productivity index. The analysis of resource utilization efficiency is conducted using a non-parametric approach, supported by the DEAP 2.1 software.

Table 1. The list of food companies used for analysis and evaluation from 2019 - 2024

Code	Name company	Code	Name company
AAM	Mekong Fisheries Joint Stock Company	DBC*	Dabaco Group
VNM*	Viet Nam Dairy Products Joint Stock Company	FMC	Sao Ta Foods Joint Stock Company
ACL	Cuu Long Fish Joint Stock Company	IDI	I.D.I International Development & Investment Corporation
ANV	Nam Viet Corporation	KDC	KIDO Group Corporation
ASM	Sao Mai Group Corporation	LAF	Long An Food Processing Export Joint Stock Company
BAF*	BAF Viet Nam Agriculture Joint Stock Company	MCM	Seed Moc Chau Dairy Cattle Corporation JSC
ABT	Bentre Aquaproduct Import and Export Joint Stock Company	MSN*	Masan Group Corporation
AGM	An Giang Import - Export Company	NAF	Nafoods Group Joint Stock Company
BBC	Bibica Corporation	PAN*	The PAN Group Joint Stock Company
CMX	Camimex Group Joint Stock Company	VHC	Vinh Hoan Corporation
DAT	Travel Investment and Seafood Development Corporation		

*Note: * The firms have published Environmental, Social, and Governance (ESG) reports*

Source: Vietstock (2025)



Source: Vietstock (2025)

Figure 1. The profits of Food Company from 2019 - 2024

3.1. Data Envelopment Analysis – DEA

In this study, the Data Envelopment Analysis (DEA) method is employed as a linear programming technique to assess how each firm performs relative to its peers within the sample. The technique constructs an efficient frontier, formed by the best-performing firms, against which the less efficient firms are benchmarked. Efficiency scores range from 0 to 1, with a score of 1 indicating a firm that is fully efficient. A basic **DEA model** is formulated as a problem of **efficiency maximization**, utilizing **output weights** (u) and **input weights** (v) for i inputs (x) and j outputs (y). By normalizing the sum of input weights to 1, the optimal efficiency score of a given company can be expressed through the following algebraic formulation:

$$\text{Max}_{uv}\,(uy_j) \text{ với } vx_i = 1$$

$$Uy_i - vx_i < 0\ ;\ u, v > 0$$

3.2. Malmquist productivity index (MPI)

The Malmquist productivity index (MPI) is employed to assess differences in efficiency either between two units or within a single unit across two time periods. To estimate changes in technical efficiency and technological progress over the study period, this research utilizes a Malmquist productivity index analysis based on the ratio of output quantities.

As explained by [16], the Malmquist Productivity Index (MPI) serves as a valuable analytical tool for measuring productivity dynamics over time. It enables the decomposition of total productivity change into two distinct components: technical efficiency change, which reflects improvements or declines in a decision-making unit's ability to utilize resources effectively; and technological change, which captures shifts in the production frontier due to innovation or advancements in technology. The combined effect of these two components yields a comprehensive, frontier-based measure of productivity change. According to [11, 27] and [28], the output-based Malmquist index of productivity change within the framework of distance function is:

$$M_0(X_{t+1}, Y_{t+1}, X_t, Y_t) = \left(\frac{d_0^t(X_{t+1}, Y_{t+1})}{d_0^t(X_t, Y_t)} * \frac{d_0^{t+1}(X_{t+1}, Y_{t+1})}{d_0^{t+1}(X_t, Y_t)} \right)^{1/2} \quad (1)$$

This represents the productivity of the production point (X_{t+1}, Y_{t+1}) relative to the production point (X_t, Y_t). Where d_0^t is a distance function measuring the efficiency of conversion of inputs X_t to outputs Y_t in the period t [29]. The value of m greater than 1 indicates positive TFP growth, whereas the value of m lower than 1 indicates a decline from period t to $t+1$.

MPI is the geometric mean of the two outputs-based Malmquist index [11]. One index uses period t technology and the other uses period $t+1$ technology [7]. Mathematically, this can be written as [11]; [27-28]:

$$M_0(X_{t+1}, Y_{t+1}, X_t, Y_t) = \left(\frac{d_0^{t+1}(X_{t+1}, Y_{t+1})}{d_0^t(X_t, Y_t)} \right) * \left(\frac{d_0^t(X_{t+1}, Y_{t+1})}{d_0^{t+1}(X_{t+1}, Y_{t+1})} * \frac{d_0^t(X_t, Y_t)}{d_0^{t+1}(X_t, Y_t)} \right)^{1/2} \quad (2)$$

In this expression, the first component on the right-hand side represents the change in technical efficiency, while the second captures the shift in technology, or technological change. Technical efficiency change refers to variations in a unit's ability to convert inputs into outputs relative to the production frontier—that is, how close actual production is to the maximum feasible output. Specifically, it measures the change in constant returns to scale (CRS) technical efficiency from period t to period $t+1$ [29]. A value greater than one indicates an improvement in technical efficiency, signifying that the unit has moved closer to the optimal production frontier over time.

Technical efficiency can be further analyzed by decomposing the change in constant returns to scale (CRS) efficiency into two distinct components: scale efficiency and pure technical efficiency under variable returns to scale (VRS). This decomposition allows for a clearer understanding of whether efficiency gains or losses are due to operating at an optimal scale or to improvements in managerial performance. The analysis relies on distance functions relative to a VRS technology, offering a more flexible benchmark that accounts for the varying returns to scale across decision-making units. The CRS and VRS values are used to calculate the scale efficiency effect.

4. RESULTS AND DISCUSSION

An output-oriented (i.e. output maximisation) Malmquist DEA involving data on two output variables as sales (Y1); operating income (Y2) and three input variables as assets (X1), operating costs (X2), SG&A (X3) for 21 firms was observed over a six-year period (2019-2024). The input and output were described in VND millions.

The DEA-Malmquist Total Factor Productivity (TFP) index is a dynamic efficiency metric used to assess productivity changes between two periods, typically from period t to period $t+1$. A Malmquist index value **equal to 1** indicates no change in productivity over time. A value **greater than 1** signifies an improvement—either due to enhanced technical efficiency, technological progress, or both—while a value **less than 1** reflects a decline in performance, indicating either reduced efficiency or technological regress. This interpretation also applies to each component of the index, where values above, below, or equal to 1 denote improvement, deterioration, or stability, respectively [11].

As 2019 serves as the base year, the Total Factor Productivity (TFP) index and its components are presented starting from 2020 onward. The average TFP change index for the period 2019 – 2024 is 0.961, indicating a 3.9% decline in TFP over the six years.

The primary cause of this decline is a **3.7% reduction in technological change** (techch), 0.3% **reduction in Technical efficiency change (effch)** although there was a **0.8% improvement in** Pure technical efficiency change (pech), it remained significantly lower than the magnitude of the **decline in technological change** observed during the same period. Looking at the productivity change over the years shows that, over the entire study period, the productivity change index increased by 12.2% in 2022 and 10.9% in 2024 compared to the reference year 2019 (Table 2). Besides, productivity declined in all other years, with the most significant drops occurring in 2023 (−18.3%) and 2021 (−11.0%). The notable increase in 2022 was primarily driven by technical efficiency change (effch**)**, whereas the modest improvement in TFP in 2014 was entirely attributable to gains in technical efficiency change (effch) and technological change (techch)

Table 2. Malmquist index summary of annual means

Year	Technical efficiency change (effch)	Technological change (techch)	Pure technical efficiency change (pech)	Scale efficiency change (sech)	Total factor productivity (TFP) change (tfpch)
2020	0.698	1.297	0.731	0.956	0.906
2021	1.295	0.687	1.215	1.066	0.890
2022	1.179	0.952	1.209	0.976	1.122
2023	0.877	0.931	0.963	0.911	0.817
2024	1.055	1.052	1.005	1.049	1.109
Mean	0.997	0.963	1.008	0.990	0.961

Source: Analysis results from DEAP 2.1 software

The Total Factor Productivity Change (tfpch) during the study period is less than 1 (TFP = 0.971), mainly reason due to the change in technological progress (techch) reaching only 0.963. This can be explained by the fact that technological progress has not yet been fully realized during this period and many companies still favor labor-intensive technologies. Thus, the factor of technological change is of great importance in contributing to the improvement of total factor productivity (TFP).

Table 3 presents the aggregated Malmquist index results, summarizing the average performance of 21 selected food companies over the 2019–2024 period. The table includes key components of productivity change: efficiency change, technical change, pure technical efficiency change, scale efficiency change, and total factor productivity (TFP) change. Among the firms analyzed, seven demonstrated an improvement in mean annual technical efficiency (effch > 1), four maintained the same level of efficiency (effch = 1), and ten experienced a decline (effch < 1). These findings suggest that only a minority of companies succeeded in enhancing their managerial efficiency—specifically their ability to convert inputs into outputs (Y1, Y2)—while the majority either stagnated or regressed in this regard.

An analysis of mean annual technological change revealed that five companies exhibited technological advancement (techch > 1), while sixteen experienced a decline (techch < 1). This suggests that a subset of companies actively modernized their operations, likely through the adoption of cutting-edge technologies to enhance service delivery. For scale efficiency change, five companies increased (*sech >1*), four companies remained unchanged (*sech =1*) and twelve companies decreased (*sech < 1*) their mean annual scale efficiency change.

Table 3. The Malmquist index summary of the firm means

Firm	Technical efficiency change (effch)	Technological change (techch)	Pure technical efficiency change (pech)	Scale efficiency change (sech)	Total factor productivity (TFP) change (tfpch)
AAM	0.963	0.955	1.000	0.963	0.919
VNM*	1.000	0.990	1.000	1.000	0.990
ACL	0.991	1.005	0.998	0.993	0.996
ANV	0.914	0.966	0.923	0.990	0.883
ASM	0.927	1.002	0.981	0.945	0.929
BAF*	0.909	0.765	0.940	0.967	0.695
ABT	1.092	0.973	1.031	1.059	1.062
AGM	1.276	0.934	1.272	1.003	1.192
BBC	0.926	0.940	0.927	0.999	0.870
CMX	0.968	1.018	0.972	0.996	0.986
DAT	1.035	0.974	1.001	1.034	1.008
DBC*	1.028	1.009	1.078	0.954	1.038
FMC	1.000	0.943	1.000	1.000	0.943
IDI	0.963	0.945	1.025	0.940	0.910
KDC	0.996	0.979	0.977	1.019	0.976
LAF	1.027	0.968	1.000	1.027	0.994
MCM	1.000	0.930	1.000	1.000	0.930
MSN*	1.000	0.984	1.000	1.000	0.984
NAF	1.016	1.006	1.047	0.970	1.021
PAN*	1.005	0.986	1.029	0.976	0.990
VHC	0.963	0.994	1.000	0.963	0.957
Mean	0.997	0.963	1.008	0.990	0.961

Source: Analysis results from DEAP 2.1 software

TFP increased for five of the food companies (ABT, AGM, DAT, DBC*, NAF) in which, DBC* is a company with ESG reporting. Among the companies with the highest TFP score increases are AGM (19.2 per cent); ABT (6.2 per cent); DBC* (3.8 per cent); NAF (2.1 per cent); DAT (0,8 per cent), respectively. Even though, their TFP is greater than 1, NAF (2.1 per cent); DAT (0,8 per cent), respectively, can be mentioned among the food companies with the lowest increase in TFP score. TFP decreased for sixteen of the food companies. Among the companies. with the highest decrease in TFP score are BAF* (30.5 per cent) and BBC

(13.0 per cent). Although both companies DBC* and BAF* have ESG reports, DBC* has TFP increased, BAF* has TFP decreased.

5. CONCLUSION

This study employed the DEA-Malmquist Productivity Index (DEA-MPI) to assess the performance of 21 food companies listed on the Ho Chi Minh Stock Exchange over the six-year period from 2019 to 2024. The objective was to evaluate whether these companies maintain superior efficiency levels based on DEA metrics. A summary of the firms' average Malmquist index results is presented in Tables 2 and 3.

The first, the analysis shows that five food companies achieved a Total Factor Productivity (TFP) score greater than 1, reflecting an improvement in their overall performance. In contrast, sixteen companies recorded TFP scores below 1, indicating a decline in productivity.

The second, among all firms, AGM demonstrated the highest productivity growth with a TFP score of 1.192, while BAF* exhibited the greatest decline, with the lowest TFP score of 0.695.

The third, in this study, there are five companies with ESG reports are: VNM*; BAF*; DBC*; MSN*; PAN* but only DBC* scored TFP above 1 is ranked in descending order in Table 3. Most of food companies with deteriorated performance (*tfpch < 1*) had a technological change score of less than 1 (*techch < 1*) except ACL; ASM; CMX; DBC*; NAF.

The result indicates that not all companies with ESG reporting have high TFP. Therefore, for ESG reports to be effective for food companys, they should:

Firstly, companys need to integrate ESG factors into their business strategies, risk management processes and performance evaluations through improving their sustainability reporting, which can help save costs and create long-term value.

Second, companies should build an appropriate and effective ESG management system from the top down. This system could include a senior management position dedicated to developing and leading all ESG activities; defining a specific agenda for discussing ESG issues at the board and executive levels; reporting mechanisms and information reported to these levels; and providing clear ESG-related performance indicators (KPIs) to determine the remuneration of the board and ESG team.

Third, the company should improve its technological infrastructure to support data mining and ESG reporting. In particular, it is possible to take advantage of 4.0 technology applications such as artificial intelligence (AI), machine learning, blockchain... to collect big data related to ESG as well as build ESG assessment indicators, serving ESG reporting.

Government intervention or official guarantees—such as issuing green certifications—are essential to enhance the credibility and impact of ESG reports on financial efficiency. Currently, ESG disclosures are voluntary, lacking strict regulatory oversight or mandatory audits. While these reports are publicly available under company names, which reduces the likelihood of outright falsification, companies may still selectively present information or adjust their activities to create a misleading impression of environmental responsibility. Regulatory support would help ensure transparency, accountability, and consistency in ESG reporting practices..

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TÓM TẮT

TÁC ĐỘNG CỦA ESG ĐẾN HIỆU QUẢ TÀI CHÍNH CỦA CÁC DOANH NGHIỆP THỰC PHẨM

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Trước tầm quan trọng ngày càng gia tăng của hiệu quả hoạt động môi trường, xã hội và quản trị (ESG) trong các tổ chức, nghiên cứu này nhằm đánh giá hiệu quả và phân tích tác động của ESG đối với các doanh nghiệp thực phẩm trong giai đoạn 2019-2024. Phương pháp phân tích năng suất tổng hợp DEA-Malmquist (TFP) sử dụng các yếu tố đầu vào và đầu ra để đo lường hiệu quả kỹ thuật và sự thay đổi công nghệ của 21 doanh nghiệp thực phẩm, trong đó có 5 doanh nghiệp công bố báo cáo ESG. Kết quả nghiên cứu cho thấy không phải tất cả các doanh nghiệp có báo cáo ESG đều đạt mức năng suất tổng hợp cao. Việc công bố báo cáo ESG hiện nay vẫn chủ yếu mang tính tự nguyện, chưa có cơ chế kiểm toán chặt chẽ đi kèm. Mặc dù báo cáo được công khai dưới danh nghĩa doanh nghiệp, hạn chế khả năng làm giả, song vẫn tồn tại khả năng các doanh nghiệp điều chỉnh thông tin về các hoạt động chưa đạt yêu cầu để tạo dựng hình ảnh "xanh hóa". Do đó, sự can thiệp hoặc bảo đảm từ phía chính phủ – chẳng hạn như áp dụng các chứng nhận xanh – là cần thiết để bổ trợ cho các báo cáo ESG, từ đó thúc đẩy các doanh nghiệp cải thiện hiệu quả tài chính một cách thực chất và bền vững.

Từ khóa: Hiệu quả hoạt động, hiệu quả kỹ thuật, phân tích bao dữ liệu (DEA), chỉ số Malmquist.