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Evaluating ESG efficiency using DEA an analysis of Dow Jones Industrial average companies

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A B S T R A C T

In today's investment climate, the integration of Environmental, Social, and Governance (ESG) factors into strategic decision-making is essential, particularly in industry performance analysis. The article employs Data Envelopment Analysis (DEA) to calculate and contrast ESG efficiency for a broad variety of industries represented in companies in the Dow Jones Industrial Average. Through adopting three other DEA methods—the Constant Returns to Scale (CCR) model and input- and output-oriented Banker, Charnes, and Cooper (BCC) models—we provide a comprehensive framework to analyze how ESG inputs are allocated across different industries to achieve stock price appreciation. The results have important variations in different sectors. For example, the Technology & Telecom, Financial Services, and Retail & Consumer Goods industries have efficiency scores calculated much higher using the input-oriented BCC approach (INBCC) compared to when the scores are derived from the CCR model. This indicates very efficient management of resources that is masked under the constant return assumption. In contrast, industries like Media and Entertainment have efficiency scores that are high across different models, while others like Aerospace and Defense perform better once, they change their priority to output maximization. The results show that the selection of DEA methodology has a strong impact on efficiency scores and that the impact differs by industry. These findings provide industry-specific benchmarks for corporate practitioners, investors, and policymakers in return for fostering sustainable practices and enhancing portfolio selection strategies.

1. Introduction

Systematic selection of stock portfolios is one of the most important areas of investment management (Kucko et al., 2007), influencing the risk-adjusted returns and long-term performance of investment funds (Giese et al., 2019). In the present investment environment, where financial success coupled with social responsibility has emerged as essential priorities for investors (Ballestero et al., 2012), the necessity of an integrated approach in portfolio selection has become increasingly apparent. Data Envelopment Analysis (DEA) has been the key approach in this area, as it enables us to quantify the relative efficiency of decision-making units (DMUs) (Charnes et al., 1977; Sun et al., 2013), e.g., organizations, based on a number of inputs and outputs (Cooper et al., 2007). The use of Data Envelopment Analysis (DEA) gives investors valuable information regarding the operating productivity of the target investments, considering both conventional financial indicators and environmental, social, and governance (ESG) criteria (Lydenberg, 2013; Rau & Yu, 2024). The increasing relevance of Environmental, Social, and Governance (ESG) factors in investment choices can be attributed to the awareness that a firm's sustainability efforts and ethical behavior can directly affect its long-term financial performance and risk assessment (Arvidsson & Dumay, 2022). Investors are now looking for investments that will not only give them good financial returns but also match their values and help build a more sustainable future (Hanson et al., 2013).

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Recently, considerable literature has grown up around the theme of ESG performance across different industries for several aspects (Wu & Xie, 2024; Shi et al., 2023; Kartal et al., 2024; Kurt & Peng, 2021) and this research aims to leverage the power of DEA to assess the efficiency of a select group of companies, the constituents of the Dow Jones Industrial Average (DJIA), in terms of their ESG performance and financial growth. By using a multi-faceted set of ESG measures as inputs and stock price appreciation rates as outputs, this research gives an overall assessment of the link between a company's sustainability practices and its market performance.

The knowledge gained from this research has the potential to influence investment decisions, assist businesses in enhancing their ESG practices, and contribute to the wider debate on the role of sustainability in financial market futures. In particular, this research aims to:
Screen the Dow Jones firms that are highly efficient in transforming their ESG inputs into solid financial growth and thus act as benchmarks for sustainable investing approaches.

Identify areas in which poor-performing business can enhance their environmental, social, and governance performances to make their competitive position and overall long-term sustainability stronger.
Provide guidance to investors on the optimal manner in which to incorporate ESG-efficient companies into their portfolios for the aim of potentially achieving improved risk-adjusted returns while adhering to their ethical and sustainability principles.
Offer policy-makers and regulators an understanding of why ESG issues are important in the financial sector and help shape reporting standards and regulatory policy to advance transparency and accountability in companies.
By achieving these goals, this research aims to bridge the gap between financial performance and sustainable business practices, thus contributing to the ongoing elaboration of responsible investment strategies and to the transition towards a more sustainable global economy.

2.The proposed method

In this section, we introduced the proposed method used in this paper, notations and formulas:

2.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a performance measurement technique used to evaluate the efficiency of decision-making units (DMUs) (Charnes et al., 1977; Sun et al., 2013), such as firms, departments, or public services. This tool is developed by Charnes, Cooper, and Rhodes (1978) and is a non-parametric method that uses linear programming to evaluate the efficiency of DMUs by comparing the ratio of outputs to inputs (Mukherjee et al., 2008; Simar & Wilson, 2000; Wang & Chin, 2009). The primary role of DEA is to identify the most efficient units in a view to benchmark and improve performance. It works through creating a best practice frontier whereby only efficient units are on the frontier and all the others under the frontier account for inefficiencies (Charnes et al., 1978). The CCR model (Charnes-Cooper-Rhodes) has consistent returns to scale; it concentrates on assessing efficient units based on an efficiency frontier of best practices, while the BCC model (Banker-Charnes- Cooper) (1984) has variable returns to scale and relaxes the analysis to allow for more flexibility for organizations that do not function at optimal efficiency (Banker & Thrall, 1992; Allahyar & Rostamy-Malkhalifeh, 2015). The BCC model has both input-oriented and output-oriented model, Output-Oriented aims to change inputs while maintaining output levels and Input-Oriented aims to change outputs for a given level of inputs that allowing analysts to choose the focus based on the specific evaluation context (Dellnitz et al., 2018).

$$\max h_k(u,v) = \frac{\sum_j u_j y_{jk}}{\sum_i v_i x_{ik}}. \tag{1}$$

where:

($h_k(u,v)$): The efficiency score for Decision-Making Unit (DMU) (k), calculated as the ratio of weighted outputs to weighted inputs.

(u_j): The assigned weight for output (j), reflecting its relative importance in efficiency measurement.

(y_{jk}): The observed output (j) for DMU (k).

(v_i): The assigned weight for input (i), representing its contribution to resource utilization.

(x_{ik}): The observed input (i) for DMU (k).

(j): Index representing outputs, where (j = 1, \dots, t).

(i): Index representing inputs, where (i = 1, \dots, m).

(k): Index denoting the DMU being evaluated.

One of the key advantages of DEA is that it has the ability to assist investors in deciding on effective portfolios(Emrouznejad & Yang, 2018) and decide how effectively companies earn profits in relation to their inputs. For sustainability measures, it enables the quantification of companies' environmental and social contributions alongside their economic performance, encouraging a holistic view of corporate efficiency. DEA allows investors to compare a number of companies simultaneously and understand which companies are operating on maximum levels of efficiency.

DEA Methods:

2.1.1 CCR Method

The CCR assumes constant returns to scale (Mehdiloozad & Sahoo, 2015). This means that if inputs are doubled, outputs will also double proportionately. The CCR model is stricter, evaluating efficiency based on comparisons with the best-performing decision-making units (DMUs). It is most suitable when we are confident that changes in scale do not affect efficiency and CCR is stricter than BCC and may identify more DMUs as inefficient.

CCR Method Formula[1]:

$$\max \sum_i u_i y_{ik} \tag{2}$$

$$s.t \quad \sum_j v_j x_{jk} = 1 \tag{3}$$

$$\sum_j v_j x_{jl} \leq \sum_i u_i y_{il} \qquad \text{where } u_{i \geq 0}\ ,\ y_{j \geq 0} \quad \text{and } l = 1,2,\dots,k$$

where:

- (i): Index representing outputs, where (i = 1, ..., n).
- (j): Index representing inputs, where (j = 1, ..., m).
- (l): Index representing different DMUs in the dataset.
- (u_i): The weight assigned to output (i), representing its relative importance in the efficiency calculation
- (y_{ik}): The observed amount of output (i) for Decision-Making Unit (DMU) (k).
- (v_j): The weight assigned to input (j), reflecting its significance in resource utilization.
- (x_{jk}): The observed amount of input (j) for DMU (k).
- (x_{jl}): The amount of input (j) for DMU (l), ensuring that constraints hold across multiple units.
- (y_{il}): The observed amount of output (i) for DMU (l), used in comparison constraints.

2.1.2 BCC Method

The BCC model has both input-oriented and output-oriented models, Out-Oriented aims to change inputs while maintaining output levels and input-Oriented aims to change outputs for a given level of inputs that allows analysts to choose the focus based on the specific evaluation context.

BCC Output-oriented Method Formula:

$$\min \sum_j v_j x_{jk} + v_0 \tag{4}$$

$$s.t \quad \sum_i u_i y_{ik} = 1 \tag{5}$$

$$\sum_i u_i y_{il} \leq \sum_j v_j x_{jl} + v_0 \qquad \text{where } u_{i \geq 0}\ ,\ y_{j \geq 0} \quad \text{and } v_{0:free}$$

[1] Definition, formulas and assumption details of CCR and BCC were explained by Cooper et al. (1978).

BCC Input-oriented Method Formula:

$$\max \sum_j u_j y_{jk} + u_0 \tag{6}$$

$$s.t \ \sum_j v_j x_{jk\,=\,1} \tag{7}$$

$$\sum_i u_i y_{il} + u_0 \leq \sum_j v_j x_{jl} \qquad \text{where } u_{i\,\geq 0}\ ,\ y_{j\geq 0} \quad \text{and } u_{0:free}$$

The notation explanations for both formulas have already been provided in *2.1.1(CCR Method)*

2.2 ESG Factors

The Environmental, Social, and Governance (ESG) metrics are core determinants of a firm's ethical footprint and sustainability (Li et al., 2021). The environmental metrics quantify the extent to which an organization manages its environmental footprint. This entails an examination of its carbon footprint, waste disposal, water pollution rate, and consumption of natural resources. These factors are paramount in ascertaining the extent to which a corporation is liable in regard to environmental matters. Social concerns address how an organization relates with its various stakeholders, ranging from employees to suppliers, customers, and surrounding communities (Friede et al., 2015). These involve a number of aspects such as the organization's labor practices, whether it espouses diversity and inclusion policies, as well as its adherence to human rights norms. Through such affiliations, shareholders can gain some insight into the company's perception of its employees and its place in society as a whole, which may also be a reflection of the company's general ethical policy down the line. Governance issues relate to the internal regulations and policies that determine the operations and decision-making of an organization. This involves an examination of such areas as the structure of the board of directors, executive remuneration plans, and the rights of shareholders. Through these elements, investors and other interested parties are able to establish the level of ethics upheld by a corporation, in addition to its potential for long-term success. Taken together, these governance elements are crucial to establishing a firm's credibility and potential for success in the business competitive landscape.

Over the last few years, ESG-related factors have played a progressively more central role in investment decision-making (Arunkumar et al., 2025). Investors have come to realize that companies prioritizing best practices in these domains are more able to contend with risks and capture upcoming opportunities (Rau & Yu, 2024). An extensive body of literature has established a positive link between ESG performance at the firm level and its financial performance. A meta-study of more than 2,000 studies by Friede et al. (2015) discovered that approximately 90% of them had noted at least a neutral relationship between ESG factors and financial performance, while many others showed a decidedly positive impact. These sorts of companies with focus on ESG values tend to suffer less market volatility, have superior operating performance, and enjoy a better reputation, which, in turn, can make their financial situation even more sound.

Investors have been advocating for enhanced transparency and accountability within corporate governance, environmental effects, and social performance. As the demand for responsible investment rises among a growing number of individuals, a notable trend has emerged that underscores the importance of sustainability performance in shaping their investment decisions (Thore & Tarverdyan, 2022). A study conducted by Friede et al. (2015) affirms that companies with good Environmental, Social, and Governance (ESG) practices possess a better capacity to create opportunities and react to risks and, eventually, perform better financially.

This is also fueled by an increasing number of regulations and standards seeking to foster corporate transparency in the context of ESG reporting. For instance, the acknowledgment of the significance of ESG factors in investment decision-making has prompted regulatory bodies to develop frameworks that encourage firms to publicly disclose their ESG practices. The requirement for transparency creates well-informed investment decisions and simultaneously compels industries to turn sustainable, thereby rendering them more accountable as stakeholders within their own communities.

So, we give the 3 social and government environmental indicators as inputs and the percentage of stock price growth as an output to the DEA method. The stock price growth is obtained from the following formula:

$$growth\ rate = \frac{current\ price - analyst\ price\ target\ avrage}{current\ price} \times 100 \tag{8}$$

The proposed method of this paper has used to 3 inputs and 1 output. *Fig 1* summarizes the structure of the proposed method:

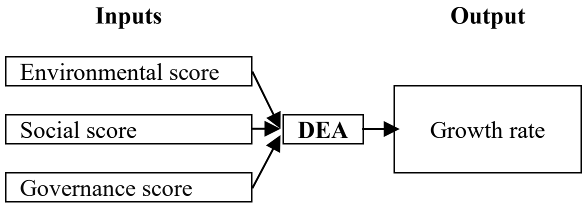

Fig. 1. The Structure of The Proposed Method

3.Results & Discussion

Also, according to past research, the effectiveness of DEA in portfolio selection has been proven. Therefore, this proposed method has been applied for firm index by Dow Jones and use ESG indicator as an input to the DEA method because Dow Jones stocks are 30 of the largest companies and their ESG index will be very vital and is a symbol of the overall condition of US listed companies, here we talking more about The Dow Jones:

The Dow Jones stock is a group of stock market indices that were developed by Dow Jones & Company to track the performance of various groups of stocks. The most prominent of these indices is the Dow Jones Industrial Average (DJIA), which consists of 30 large publicly traded United States companies that are recognized to be industry leaders. The Dow Jones indices are an accepted standard employed in the evaluation of market trends and general economic status, hence boosting investor confidence and investment activities. (Cerin & Dobers, 2001).

Dow Jones indices are utilized globally and shape investment decisions on a global basis (Giannarakis et al., 2017), thereby affecting the general direction of financial markets.

Table 1
30 Dow Jones firms list

Industry	Companies	Stock	Additional Details
Technology & Telecom	Apple Inc.	AAPL	Consumer electronics and software (iPhone, Mac, iOS)
	Cisco Systems, Inc.	CSCO	Networking solutions and cybersecurity
	IBM	IBM	Cloud computing, AI, and IT services
	Intel Corporation	INTC	Semiconductor and microprocessor manufacturer
	Microsoft Corporation	MSFT	Software, gaming, and cloud services (Azure)
	Salesforce, Inc.	CRM	Cloud-based CRM software and business solutions
	Verizon Communications Inc.	VZ	Telecommunications, internet, and wireless services
Financial Services	American Express Company	AXP	Banking, credit cards, and financial transactions
	Goldman Sachs Group, Inc.	GS	Investment banking and asset management
	JPMorgan Chase & Co.	JPM	Banking and financial investment services
	Visa Inc.	V	Payment technology and card services
Industry & Energy	3M Company	MMM	Industrial and consumer products
	Caterpillar Inc.	CAT	Heavy construction and mining equipment
	Chevron Corporation	CVX	Oil and gas production and distribution
	Dow Inc.	DOW	Chemicals and specialty materials
Retail & Consumer Goods	The Home Depot, Inc.	HD	Home improvement and building supplies
	Nike, Inc.	NKE	Sports apparel and footwear
	Procter & Gamble Company	PG	Household and personal care products
	Walgreens Boots Alliance, Inc.	WBA	Pharmacy services and healthcare retail
	Walmart Inc.	WMT	Discount retail and e-commerce
Aerospace & Defense	Raytheon Technologies Corporation	RTX	Aerospace and defense systems
	Boeing Company	BA	Commercial and military aircraft production
Media & Entertainment	The Walt Disney Company	DIS	Movies, television, streaming, and theme parks
Insurance	The Travelers Companies, Inc.	TRV	Property and casualty insurance
Food & Beverage	McDonald's Corporation	MCD	Fast Food/Restaurants (Quick Service Restaurants)
	Coca-Cola Company	KO	Beverages (Non-Alcoholic Beverages, Soft Drinks)
Healthcare & Pharmaceuticals	Johnson & Johnson	JNJ	Pharmaceuticals and medical devices
	Merck & Co., Inc.	MRK	Biopharmaceuticals and medical research
	UnitedHealth Group Incorporated	UNH	Healthcare services and insurance
	Amgen Inc.	AMGN	Biotechnology and pharmaceutical development

Table 1offers an overview of 30 companies grouped by industry with details of their sectors. To help illustrate this breakdown, the pie chart below offers a graphical overview of these industries and the proportion of companies within each grouping. The graphical presentation assists in understanding industry breakdowns by means of company composition within different sectors.

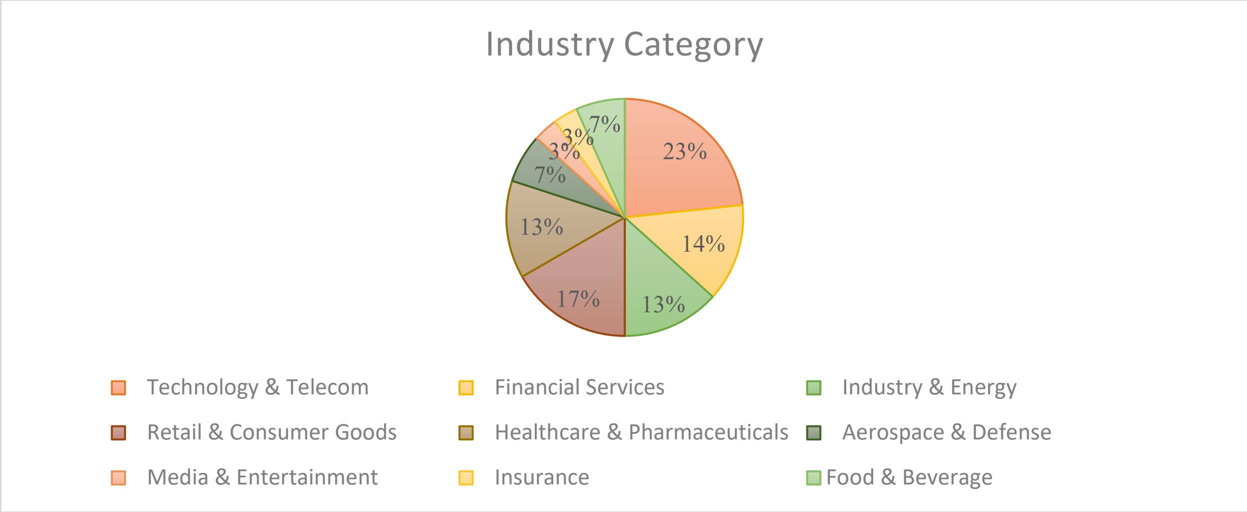

Fig. 2. Industry Category

On March 6, 2025, we extracted data on the ESG (Environmental, Social, and Governance) risk index of Dow Jones companies, along with the corresponding current price and target price. The collected data is presented in the table below, showcasing the key metrics that reflect both the current market conditions and the sustainability performance of the companies analyzed.

Table 2

ESG scores and price information

Industry	Stock Symbol	environmental	social	governance	total	current p	target	growth rate
Technology & Telecom	AAPL	0.60	7.30	8.50	16.40	234.55	252.92	7.832018759
	CSCO	0.40	7.60	4.90	12.90	63.08	70.41	11.62016487
	IBM	1.60	6.70	5.00	13.30	248.1	254.51	2.583635631
	INTC	7.70	6.90	4.60	19.20	20.82	22.77	9.365994236
	MSFT	1.60	7.60	4.30	13.50	395.9	507.05	28.07527153
	CRM	2.00	8.20	5.00	15.20	287.77	379.92	32.02210098
	VZ	4.10	10.10	5.10	19.30	43.71	47.68	9.082589796
Financial Services	AXP	0.10	9.70	8.40	18.30	276.71	317.04	14.57482563
	GS	0.80	13.50	11.00	25.20	571.25	650.62	13.8940919
	JPM	2.40	14.00	10.80	27.30	245.55	267.21	8.82101405
	V	1.90	8.30	5.20	15.40	342.55	373.81	9.125675084
Industry & Energy	MMM	19.50	16.50	6.50	42.90	146.47	154.41	5.420905305
	CAT	10.20	11.80	6.40	28.30	337.73	391.13	15.81144701
	CVX	19.90	10.60	7.80	38.40	151.64	176.76	16.56554999
	DOW	12.20	3.40	4.30	20.00	37.02	45.29	22.33927607
Retail & Consumer Goods	HD	3.40	6.50	2.70	12.60	384.54	431.96	12.331617
	NKE	3.00	10.00	5.40	18.40	77.62	86.04	10.84771966
	PG	8.50	10.80	5.70	24.90	173.99	178.62	2.661072475
	WBA	1.9	8.50	5.20	15.60	10.66	11.78	10.5065666
	WMT	7.2	11.6	6.4	25.3	95	108.47	14.17894737
Aerospace & Defense	RTX	7.70	15.30	6.80	29.80	127.89	142.23	11.21276097
	BA	7.90	22.20	6.50	36.50	158.90	195.81	23.22844556
Media & Entertainment	DIS	0.1	8.50	5.90	14.50	105.9	126.43	19.38621341
Insurance	TRV	0.80	10.40	9.20	20.40	256.09	269.15	5.099769612
Food & Beverage	MCD	8.40	12.50	4.60	25.60	309.37	328.36	6.138281023
	KO	9.20	10.60	4.30	24.20	69.66	74.28	6.632213609
Healthcare & Pharmaceuticals	JNJ	0.90	13.00	6.10	20.10	164.84	169.07	2.566124727
	MRK	2.90	11.40	5.70	20.00	93	112.29	20.74193548
	UNH	0.10	11.90	4.60	16.60	480.85	635.32	32.12436311
	AMGN	1.8	14.9	6.1	22.8	316.69	315.95	-0.233666993

*Note:Company AMGN has been removed from the calculations due to its negative projected growth and inconsistency with the model.

According to the recent formulas related to the CCR model we provide in *2.1.1(CCR Method)*, the formulas are written in the form of linear programming in MATLAB software, and the 3 ESG indicators are given as inputs and the growth rate as outputs to the model, and the following table is obtained as the results.

Table 3

Efficiency Scores According to CCR Method

Industry	Stock Symbol	E-CCR
Technology & Telecom	AAPL	0.3486
	CSCO	0.5226
	IBM	0.0994
	INTC	0.3281
	MSFT	1
	CRM	1
	VZ	0.2679
Financial Services	AXP	0.5546
	GS	0.3477
	JPM	0.1783
	V	0.2872
Industry & Energy	MMM	0.1199
	CAT	0.376
	CVX	0.3537
	DOW	1
Retail & Consumer Goods	HD	0.6635
	NKE	0.3055
	PG	0.0707
	WBA	0.3252
	WMT	0.338
Aerospace & Defense	RTX	0.2426
	BA	0.5117
Media & Entertainment	DIS	0.8395
Insurance	TRV	0.1608
Food & Beverage	MCD	0.1911
	KO	0.223
Healthcare & Pharmaceuticals	JNJ	0.0656
	MRK	0.5465
	UNH	1

Both BCC models, namely output-oriented and input-oriented, have been formulated in MATLAB into a linear programming model and three ESG indicators have been given as inputs and growth rates as outputs to the models, and the following table has been extracted from the results.

Table 4

Efficiency Scores According to BCC Method

Industry	Stock Symbol	E_INBCC	E_OUTBCC
Technology & Telecom	AAPL	1	1
	CSCO	1	1
	IBM	1	1
	INTC	0.793	0.3291
	MSFT	1	1
	CRM	1	1
	VZ	0.661	0.2832
Financial Services	AXP	1	0.6103
	GS	0.5713	0.4325
	JPM	0.5067	0.2746
	V	0.8442	0.2874
Industry & Energy	MMM	0.4154	0.1687
	CAT	0.5025	0.4922
	CVX	0.4562	0.5162
	DOW	1	1
Retail & Consumer Goods	HD	1	1
	NKE	0.6944	0.3382
	PG	0.5553	0.0829
	WBA	0.832	0.328
	WMT	0.5442	0.4415
Aerospace & Defense	RTX	0.4254	0.349
	BA	0.5763	0.7231
Media & Entertainment	DIS	1	1
Insurance	TRV	0.712	0.1609
Food & Beverage	MCD	0.587	0.1911
	KO	0.6279	0.2297
Healthcare & Pharmaceuticals	JNJ	0.7315	0.0799
	MRK	0.6712	0.646
	UNH	1	1

In order to facilitate comparison of the performances of various industries, the efficiency scores of each sector were calculated using three alternative Data Envelopment Analysis (DEA) methods: the constant returns to scale CCR method, the input-oriented BCC method (INBCC), and the output-oriented BCC method (OUTBCC).

Table 5
ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.560439	2	0.780219559	9.432052	0.000202	3.105157
Within Groups	6.948482	84	0.08272002			
Total	8.508921	86				

Note: Based on the results of the ANOVA test and the following table, there is a significant difference between the three groups of data: CCR, In-BCC, and Out-BCC (*F* is bigger than *F crit*). This significant difference indicates substantial variation among the mean values of these three categories of data.

Separate efficiency scores for every industry were derived from the business data, and then the average efficiency score of every analytical method was calculated. The average efficiency scores, as presented in the table below, give us a common measure of performance for industries. In this way, comparative analysis of how industries allocate their resources in relation to their outputs is made explicit, based on a range of appraisal measures. For instance, industries that have above-average efficiency by the INBCC method can reflect good capability in managing inputs regardless of the possibility that their output levels are yet to be expanded. Conversely, close values among the CCR and OUTBCC methods within an industry may suggest that output maximization is less difficult than increasing input utilization. The proposed methodology is thoroughly corroborated by the established body of literature on Data Envelopment Analysis (DEA) (Banker et al., 1984; Cooper et al., 2007) and has found extensive application in studies assessing efficiency and performance benchmarks. Consequently, the computed averages function as reliable metrics for discerning both strengths and opportunities for enhancement within each sector, thereby providing valuable insights for strategic resource distribution and management strategies. The findings show that the traditional CCR method tends to produce lower efficiency scores compared to input-oriented BCC than compared to the output-oriented BCC method, which tends to provide results closer to the CCR values in a variety of sectors. For example, the CCR efficiency of the Technology & Telecom industry is approximately 0.51, whereas the INBCC measure goes up to 0.92 and the OUTBCC approach yields approximately 0.80. Such differences imply that the returns to scale assumption plays a significant role in terms of measuring performance, as established in the DEA literature too (Banker et al., 1984).

Table 6
Average industry efficiency

Industrial	**efficiency average of CCR method**	**efficiency average of**	**efficiency average of**
Technology & Telecom	0.509514286	0.922	0.801757143
Financial Services	0.34195	0.73055	0.4012
Industry & Energy	0.4624	0.593525	0.544275
Retail & Consumer Goods	0.34058	0.72518	0.43812
Aerospace & Defense	0.37715	0.50085	0.53605
Media & Entertainment	0.8395	1	1
Insurance	0.1608	0.712	0.1609
Food & Beverage	0.20705	0.60745	0.2104
Healthcare & Pharmaceuticals	0.537366667	0.8009	0.5753

The information in the table is shown in the chart below:

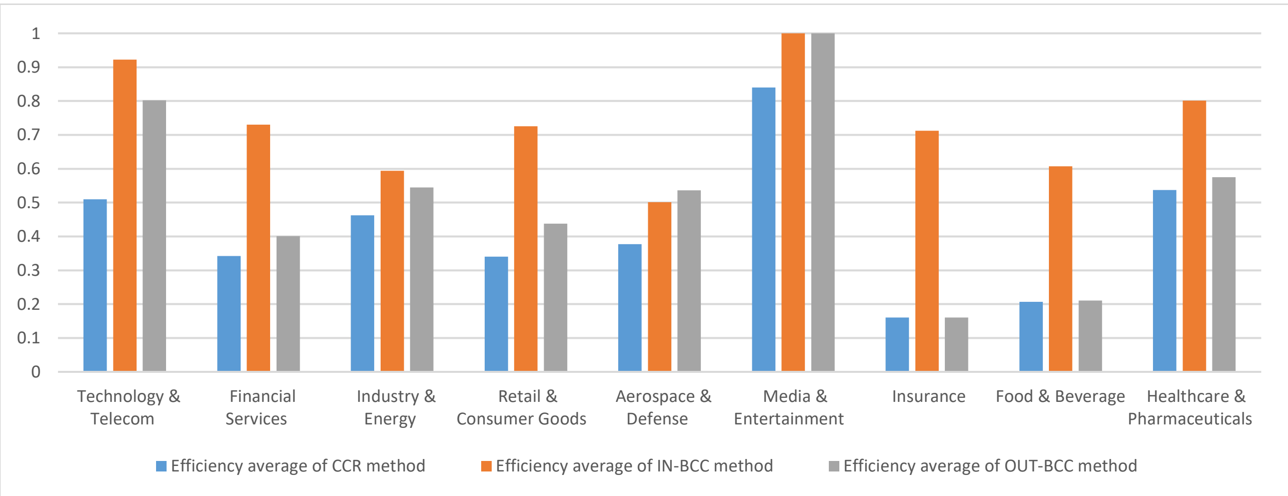

Fig. 3. The Results of Models

3.1 Industry-Specific Results

1. Technology & Telecom: The moderate CCR score (0.51) suggests that under constant returns to scale, the industry is moderately efficient. But the very high increase under the INBCC method (0.92) suggests that the industry is very good at controlling its inputs, a finding obscured under constant returns-to-scale assumptions. The marginal decrease in OUTBCC score (0.80) could be due to limitations in output maximization in spite of efficient input use.

2. Financial Services, Retail & Consumer Goods: For these sectors, the INBCC method exhibits much greater efficiency scores (0.73 for both sectors) than the CCR (0.34 for both) and OUTBCC (0.40 and 0.44) methods. This disparity implies that these sectors may be more efficient in resource utilization when measured from an input point of view. It implies that there could be hidden potential within these sectors that is revealed when variable returns to scale are taken into account (Dellnitz et al., 2018).

3. Industry & Energy and Healthcare & Pharmaceuticals: For these sectors, discrepancies among the three approaches are not that broad. A 0.46 (CCR) rises to around 0.59–0.57 through INBCC and OUTBCC methods in Industry & Energy, and a parallel pattern is observable in Healthcare & Pharmaceuticals (CCR 0.54, INBCC 0.80, and OUTBCC 0.58). This comparatively modest divergence suggests that these industries may have the potential to display operation conditions less vulnerable to the return to scale assumptions, perhaps due to the greater uniformity typical of scale effects across such facilities.

4. Aerospace and Defense: The industry has CCR efficiency of 0.38, with an improvement using INBCC at 0.50, and a further improvement using OUTBCC at 0.54. The marginal improvement indicates that the industry's efficiency would be better if efforts were put in the direction of output maximization, as indicated by the marginal difference between output orientation (OUTBCC) and input orientation.

5. Media and Entertainment: Surprisingly, this sector has very high efficiency ratings across all methods (CCR at 0.84 and 1.0 for both INBCC and OUTBCC), indicating the units within this sector are producing in very close proximity to the efficiency frontier. The fact that the high performance is consistent across different models indicates that there are good resource management skills and an excellent ability to transform inputs to outputs under different scale considerations.

6. Insurance and Food & Beverage: Both industries show a significant divergence in their approaches. Even though the CCR and OUTBCC scores are well below average (around ranging from 0.16 to 0.21), the INBCC scores are much higher, with Insurance being around 0.71 and Food & Beverage around 0.61. This stark difference would suggest that the industries are more efficient at utilizing inputs than they are at transforming these inputs into outputs—a result that is consistent with previous findings that have indicated that input-based models are more effective at identifying the expertise that relates to the management of internal resources. (Khan & Kaur, 2024). This trend may represent an inefficiency in the external market or the output measure rather than an inefficiency in internal processes.

3.2 Methodological Considerations

The emphasized disparities highlight the importance of choosing an appropriate DEA form for estimating efficiency. The constant return to scale assumption of the CCR form may indeed prove too simplistic in non-constant scale efficiency industries. The INBCC methodology, however, with variable returns to scale, seems to embrace more accurately the potential for input efficiency. In other papers like Banker et al.(1984), authors have speculated that input orientation can catch efficiencies masked by assumption 2 of constant returns. It is not so, however, in the OUTBCC method whose scores, if anything, become very close to the scores of the CCR model if output performance itself is not a main source of efficiency.
Briefly, the analysis shows that the efficiency scores are highly sensitive to the selected DEA method:
The performance of the CCR model will provide a conservative estimation because it assumes constant returns to scale.
The general success of INBCC shows great potential for expansion, particularly with various industries—most notably, Financial Services, Retail and Consumer Goods, Insurance, and Food and Beverage—receiving substantial benefits from input-based insights.

OUTBCC performance can be compared to the CCR scores in most industries, except for those industries that are primarily output maximization-based, i.e., Aerospace & Defense and Media & Entertainment.
This distinction implies that decision-makers and managers should make reflective decisions on the model of assessment based on the pertinent attributes and operational objectives of their specific industries. Future scholarship is encouraged to explore the impact of such methodological disparities on long-term strategic choices and operational enhancements. These findings are critical to the development of performance measurement systems and overall performance maximization.

5. Conclusion and Recommends

This research illustrates that it is possible to incorporate Environmental, Social, and Governance (ESG) considerations in portfolio choice using Data Envelopment Analysis (DEA). Using both the standard CCR model, with constant returns to scale, and the more versatile Banker, Charnes, and Cooper (BCC) models (input- and output-oriented), the work finds considerable variations in efficiency scores among the 30 companies of the Dow Jones Industrial Average. For instance, the Technology & Telecom sector exhibited a far greater level of efficiency when seen through the lens of the input-based

BCC (INBCC) model than the more conservative estimates presented by the CCR model. This indicates that, under variable returns to scale, certain sectors have a greater potential to leverage their ESG-related assets in an efficient way.

However, industries like Financial Services, Retail & Consumer Goods, Insurance, and Food & Beverage exhibited higher differences between input management and output realization. These results suggest that the approach employed to measure efficiency significantly influences the inferences made about industry performance. Furthermore, the finding of the positive correlation between good ESG practices and better market performance builds on previous studies (e.g., Friede et al., 2015; Hanson et al., 2013) and corroborates the perception that sustainable business practices are not only socially valuable but also economically valuable. This study effectively fills the gap between the sustainability measures and the financial performance, highlighting the necessity of a model-driven, granular analysis for the precise estimation of corporate performance in today's socially responsible investment environment.

Finally, we have outlined some recommendations for different investor groups based on the findings of this research:

For Investors: Investors should include ESG performance metrics in their portfolio selection parameters. Using the DEA model presented in this paper, investors can screen companies that efficiently convert ESG inputs into high-quality stock price returns and, therefore, guarantee both improved risk-adjusted returns and socially responsible values. This analysis technique provides an accurate benchmark for the evaluation of companies from different industries.

For Corporate Practitioners: Companies with lower efficiency scores particularly those working in sectors such as Insurance and Food & Beverage should conduct an overall review of their ESG strategies and business practices. By embracing the best practices identified among high-performing peers, these organizations can improve their resource management and output productions. More precisely, tailoring improvements in environmental sustainability, social engagement, and governance standards can result in improved market performance.

For Policymakers and Regulators: The regulatory bodies have an incentive to develop and implement standardized ESG disclosure frameworks in support of greater transparency. Standardized reporting standards will not only facilitate more robust cross-company comparison via DEA but also incentivize companies to advance their sustainability practice further. Such efforts can lead to greater market trust and a sounder financial system. For Future Researchers: Future studies should expand on the current methodology by applying DEA to additional industry types and geographical areas. Additionally, testing additional DEA models and including qualitative assessments of ESG practices could yield more insightful conclusions regarding the relationship between sustainability and financial performance. Research that continues to explore the effect of different orientations of DEA (input vs. output) on efficiency scores will be beneficial, as demonstrated by Khan and Kaur (2024) and Dellnitz et al. (2018).

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