Environmental and Ecological Statistics (2025) 32:675–706
https://doi.org/10.1007/s10651-025-00659-5

Determinants of sustainability performance of manufacturing companies using two-stage data envelopment analysis

Kristina Sutiene[1] · Clara B. Vaz[2,3] · Raminta Vaitiekuniene[1,4]

Received: 11 July 2024 / Revised: 2 April 2025 / Accepted: 6 April 2025 /
Published online: 28 April 2025

Abstract
The investigation of business performance via the lens of sustainability has become an increasingly attractive topic among scholars. This study contributes to the field by proposing a two-stage methodology. First, to assess companies' efficiency in terms of sustainability, their scores of the environmental, social and governance (ESG) pillars are combined into the single weighted sustainability performance indicator using the 'Benefit of the Doubt' model, which is maximized for each company by comparing it against the best performers in terms of ESG scores based on Data Envelopment Analysis. Then, in the second stage, the significant determinants are identified after efficiency estimates are regressed on company performance indicators using Tobit panel regression. To demonstrate this approach, we selected 559 companies from the manufacturing sector, as this industry continues to face challenges to reduce environmental impact, improve resource efficiency, and promote social responsibility. The main findings include the examination of the best performers and underperforming companies in terms of sustainability, along with key financial indicators identified in the study.

Keywords ESG · Manufacturing companies · Sustainability · Tobit panel regression · Two-stage DEA

Kristina Sutiene, Clara B. Vaz and Raminta Vaitiekuniene have contributed equally to this work.

Handling Editor: Luiz Duczmal.

Extended author information available on the last page of the article

1 Introduction

There exist several directives, initiatives, and regulatory frameworks that lead to a better world, living and working. The European Green Deal adopted in 2019 on the initiative of the European Commission includes a comprehensive set of climate change and environmental regulations. A climate-neutral continent is not only an aspiration, but also a necessity. The European Green Deal includes various policy initiatives that target a wide range of sectors, including energy, agriculture, industry, and transportation, with the aim of promoting sustainability and environmental protection (Fetting 2020). The worldwide comparison is the 2030 Agenda for Sustainable Development, which is adopted by every member of the United Nations in 2015. Central to this agenda are the 17 sustainable development goals (SDGs) that address global challenges including poverty, inequality, climate change, environmental degradation, peace, and justice (Assembly 2015). In general, the SDGs provide a comprehensive framework for sustainable development that encompasses economic, social, and environmental dimensions.

Environmental, social, and governance (ESG) criteria offer a structured framework for companies and investors to evaluate and implement sustainable practices that align with SDGs and Green Deal (Khaw et al. 2024; Leung et al. 2025; Li et al. 2025). Studies show that many conventional fund managers integrate ESG information into their responsible investing strategies to support the transition to a lower-carbon economy (Duuren et al. 2016; Pedersen et al. 2021). Furthermore, ESG criteria in particular have been used for red flagging and managing investment risks. Both financial (pecuniary) and ethical or impact-driven (non-pecuniary) motives strongly influence ESG asset allocations (Giglio et al. 2025). Most researchers recognised that ESG, as non-financial reporting, serves as an important instrument for understanding, measuring, and comparing company's development (Chai et al. 2023; Lin et al. 2025; Sun and Xiong 2025). For example, ESG disclosure has been found to have a positive impact on corporate financial performance, value, social capital, or stakeholder relations (Lins et al. 2017; Duan et al. 2025). Comparatively, Arthur et al. (2025) indicated that although higher ESG scores boost sales and lower operating costs, they also correlate with rising labor expenses, underscoring a potential trade-off in productivity. As highlighted by Beckmann and Rogmann (2024) and Giglio et al. (2025), non-financial reasons have become increasingly important, alongside financial considerations, for both companies and investors. Society tends to favor companies that allocate their financial returns to public needs, such as ethical initiatives, climate resilience efforts, and other social responsibilities. Increasing ESG indicators over the years suggest the long-term sustainable growth of companies (Chen et al. 2023; Zhu et al. 2025). This enables better opportunities for external financing, particularly access to green finance borrowing on better terms. It also promotes greater confidence among investors, employees, and the public.

Not all companies, especially with private capital, open data to the public and measure sustainability. The Corporate Sustainability Reporting Directive (CSRD) (entered into force on 5th January 2023) obliges companies to submit sustainability reports from 2025 for the previous financial year (European Commission 2023). This commitment of companies will enable wider access to information and data for assessing their impact on environmental protection, public welfare, operational risks, and opportunities. Before mandatory corporate sustainability reporting, the data sample of research is based on companies that already report sustainability indicators publicly.

As sustainability gained such importance, researchers began to explore the relationship between ESG and corporate financial performance from both directions, i.e. ESG impact on financial performance, or vice versa (Brogi and Lagasio 2018; Abdi et al. 2021; Buła et al. 2024). As highlighted in the meta-analysis performed by Whelan et al. (2021) after examining the 1000 plus individual studies, many studies indicated a positive correlation between ESG and corporate financial performance. This paper contributes to the field by proposing a two-stage methodology to investigate the sustainability performance of companies, alongside their financial indicators. For this purpose, we focus on companies from the manufacturing sector, which is one of the most problematic in terms of sustainability. In particular, this sector is responsible for around 20–30 percent of global greenhouse gas emissions (International Energy Agency 2024). The manufacturing sector also covers a wide range of key aspects, such as resource efficiency and waste reduction, environmental impact mitigation, adoption of sustainable practices (circular economy initiatives, green supply chain management), innovation and technology advancement, global impact, etc. (Abdul-Rashid et al. 2017; Incekara 2022). However, this sector undoubtedly needs to gradually shift toward green manufacturing through innovation. For example, Zheng et al. (2025) argue that large, highly polluting enterprises adopting green manufacturing will face fewer financing constraints and contribute more to environmental transformation disclosure. As manufacturing leaders increasingly recognize the value of ESG performance, it is becoming an integral part of business strategy, driving efforts to implement sustainability goals in real production processes (Chen et al. 2025b). At the same time, this sector plays a crucial role in economic growth, contributing significant added value globally.

The first contribution of this study is to combine the three pillars of the ESG score into a single sustainability performance (*CI*) score between 0 and 1 (or 0% and 100%), using the 'Benefit of the Doubt' (BoD) model (Cherchye et al. 2007) with weight constraints based on the Data Envelopment Analysis method. Basically, a restricted BoD model enables us to endogenously determine the weight assigned to each ESG indicator. This model maximizes the weighted average score for a given company by comparing the assessed company against the best practice frontier. This frontier is constructed from a linear combination of the best performing companies, in which high levels of ESG indicators are observed. Obtaining a single sustainability performance score for each company facilitates the exploration of its determinants in the next stage. This enables the identification of company performance indicators that drive sustainability performance in manufacturing companies. Measuring the connection between companies' key performance indicators (return on assets, return on equity, or gross profit margin) and sustainability indicators (energy usage, water usage, or waste management) is a challenging task. This requires comprehensive timely data and appropriate methods. Furthermore, the second contribution of this study is to identify the drivers of sustainability performance through Tobit panel regression, effectively addressing this challenging task. Thus, this study aims to assess the sustainability performance of 559 manufacturing companies using data from 2016 and 2019 and to identify financial drivers over time. These contributions are innovative in the context of the literature on assessing ESG performance in manufacturing companies.

2 Literature review

2.1 Corporate performance indicators and ESG

Corporate performance indicators (CPIs) are specific indicators that are used to assess and measure the overall performance of a company to achieve strategic goals. These indicators provide insight into various aspects of business performance and help make management decisions (Varisco et al. 2018).

Financial indicators (FIs) are one of the most important indicators among CPIs when evaluating the financial performance of a company (Chen et al. 2022). Financial ratios can measure revenue growth over time, a company's profitability after all expenses or return on investment. Therefore, financial indicators can be grouped into groups of profitability, liquidity, efficiency, and turnover. Profitability indicators are among the most significant for evaluating the company's financial performance. Many authors at all times included profitability indicators in their research to evaluate the performance of companies (Spaliara 2011; Iotti et al. 2024). However, it is not enough to evaluate performance indicators in order to achieve the sustainability of the company.

Environmental, social and governance indicators (ESG indicators) can help assess a company's sustainability and progress in sustainable activities. Environmental indicators evaluate the impact on the environment of corporations (it could be carbon footprint, energy consumption, waste management and/or use of renewable resources) (Kim et al. 2022). Social indicators measure the relationships between a company and its employees, suppliers, communities, and customers (Aljamal et al. 2024). These indicators can include social issues related to human rights, labor standards, and diversity. Governance indicators evaluate adherence to ethical standards, management structure, and leadership in the corporation (Qiu et al. 2023b). More specifically, governance sustainability criteria refer to management practices and transparency of manufacturing companies. Companies with high governance sustainability scores typically have competent independent boards that actively support and integrate sustainability objectives into their business models. These companies disclose their sustainability achievements in annual reports, and ESG data is publicly available and accessible. Manufacturing companies that implement governance practices have established anti-corruption policies, clearly defined shareholder rights, clear responsibilities, and transparent remuneration schemes for managers. A comprehensive assessment of ESG indicators in manufacturing companies can serve as a key factor in investment decisions, reputation management, partnerships, and ensuring legal compliance. Although ESG components have varying impacts on corporate innovation performance, overall, ESG can drive high-quality development (Sun and Xiong 2025). For example, the findings of Lei and Tu (2025) suggest that improvements in ESG practices strengthen innovation capabilities, with companies displaying tendencies such as reference dependence, loss aversion, and diminishing marginal utility, particularly in highly polluting industries. Comparatively, Xue et al. (2025) examined the causal relationship between climate change and the ESG performance of Chinese manufacturing firms listed between 2009 and 2021. The study found that climate change influences ESG improvements primarily through cost reduction and reputation management channels. This highlights the importance of analyzing financial ratios and sustainability indicators together to effectively assess companies' progress toward implementing the Green Deal.

One of the reasons for analyzing financial and sustainability indicators together is a more comprehensive understanding of a company's overall health and long-term viability. In fact, the question of how compatible ESG criteria are with corporate financial performance has remained a central debate for practitioners and academics alike for more than 40 years as argued by Friede et al. (2015). The implementation of the Green Deal also requires long-term strategic decisions and financial capabilities of the company. Quite a lot of investments are needed in renewable energy, energy-saving infrastructure, sustainable production, and the transport sector. The European Commission estimated that at least 1 trillion euros in sustainable investment is needed to meet the Green Deal targets (European Commission (2023)). Especially the manufacturing sector plays a significant role in the implementation of the European Green Deal, as this sector consumes a large amount of raw materials and energy (Kunecová et al. 2024).

The manufacturing industry is a crucial sector of the global economy, encompassing both heavy and light industries, as well as high-tech manufacturing, which transforms raw materials and components into finished products. This sector generates numerous jobs, supports economic growth, and drives innovation and technology worldwide. The growth in total factor productivity, particularly within the manufacturing industry, is a key driver of economic expansion (Qiu et al. 2023a). However, growing production volumes without sustainable innovation can increase pollution levels. If pollution is not controlled, the rising production volume of manufacturing enterprises can seriously undermine sustainability ambitions. As shown in Fig. 1, the manufacturing sector's global carbon dioxide emissions are among the highest of all sectors (around 6 billion tonnes of CO_2 per year).

In the manufacturing sector, environmental sustainability is recognized as one of the most important aspects of overall sustainability. Therefore, manufacturing companies should implement practices such as recycling, energy efficiency in equipment, and the efficient use of energy in their operations (Beiner 2025). Despite efforts to integrate digital technologies, automation, and sustainability principles, sustainability remains a long-term challenge in this sector. Industries such as oil refining, aerospace and defense, automobile and shipbuilding, textile and clothing

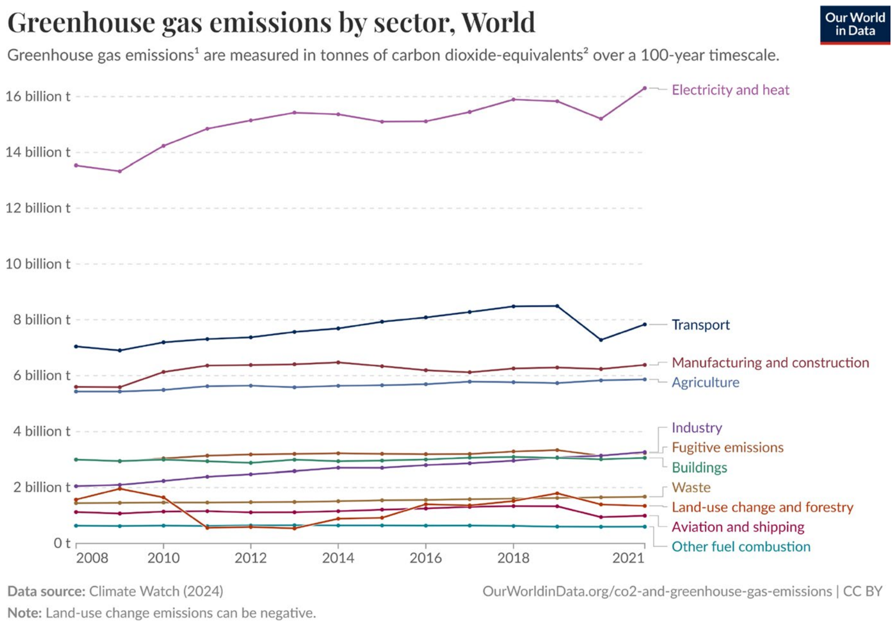


Fig. 1 CO_2 emissions by sector. Source: (Our World in Data 2024)

production, food processing, and electronics manufacturing consume large amounts of energy, emit significant quantities of carbon dioxide and waste, rely on fossil fuels, deplete water resources, and harm air, water, and soil quality. However, sustainable and green innovations can help mitigate the environmental impact of the manufacturing sector. Companies that successfully balance sustainability with profitability and invest in sustainable production methods can serve as models for others still grappling with the sustainability-profit dilemma. Therefore, the interaction between sustainability and financial performance in the manufacturing sector was chosen to be analyzed in this study. Overall, to achieve the climate neutrality goals of the Green Deal will require significant reductions in emissions within the manufacturing sector. Transitioning to sustainable production methods can greatly reduce environmental impact by using resources more efficiently and applying circular economy principles. Additionally, as highlighted by Liu and Zheng (2025), stronger pollution control measures can encourage manufacturing companies to pursue green technological innovation. As Chen et al. (2025a) highlighted, ESG has a significant impact on the stability of firms' innovation. This impact is particularly strong in firms with higher corporate governance and limited external financing, especially in polluting companies. Barman and Mahakud (2025) indicated that stronger ESG performance drives higher investments, even in the face of energy uncertainty. Lower operating costs, a stronger reputation, and sustainability practices are closely interrelated, helping companies mitigate the effects of energy and oil price fluctuations, ensuring that investments remain viable.

The analysis of the connection between corporate financial performance and sustainable indicators, namely ESG, in the manufacturing sector is discussed in different articles in the long-term period (Iwata and Okada 2011; Chen et al. 2022). The financial performance of the company expressed as the return on assets, the return on equity and Tobin's q is a frequently used parameter (Iwata and Okada 2011; Ben Lahouel et al. 2020). A higher return on assets indicates a more efficient use of corporate assets to generate net profit. Higher earnings can give a business more possibilities to expand and better investor expectations. Tobin's q coefficient, which indicates the relationship between market valuation and intrinsic value, enables us to assess whether a particular business or market is overvalued or undervalued. Many other financial indicators, such as the return on sales, net profit, profit margin, leverage ratio, or return on invested capital, reflect financial performance that should be explored together with sustainability issues (Baah et al. 2021). The authors analyze sustainable factors in connection with financial performance from different perspectives: environmental, social, governance, or newly added environmental responsibility (which represents a company's environmental performance as well). Environmental protection through greenhouse gas emissions, energy efficiency, solid waste, recycling, and water use is probably the most relevant problematic issue in many researches, especially where the aspect of the Green Deal is studied. However, research findings provide different results and interpretations of the connection between financial performance and sustainable indicators, since there are positive, negative, and neutral relationships (Iwata and Okada 2011; Chen et al. 2022; Javeed et al. 2022). Sustainability indicators have a positive influence and significantly improve the financial and economic performance of companies (Liu and Zhang 2017; Mahmood et al. 2018). Green committees representing corporate sustainability activities have a negative correlation between green performance and financial performance (Liao et al. 2015). The Environmental Protection Committee, the Social Affairs Committee or the Sustainability Board Committee as an expression of the company's commitment to sustainability are not significant for the implementation of complex solutions (Michelon and Parbonetti 2012; Rupley et al. 2012; Rodrigue et al. 2013). ESG indicators can have both positive and negative financial consequences for companies. Increased expenses, decreased income, or reduced asset values can be treated as negative consequences. However, investments that facilitate the transition to low-carbon technologies and reduce energy costs can have positive financial impacts. Overall, this demonstrates the difficulty in reaching a consensus. These ambiguities highlight the need for new decision-making models.

2.2 Methods

2.2.1 Panel regression

Since this type of research typically relies on panel data, opting for panel regression becomes a straightforward decision, making it one of the most prevalent methodologies. Panel regression utilizes both time-series and cross-sectional dimensions of the data, allowing us to control for various sources of variation observed in the data and obtain robust estimates of relationships between variables. For instance, in the study of Mazzioni et al. (2024), panel regression with fixed effects controlled by year and economic sector was used to uncover the factors that influence ESG performance and each of its pillars of companies operating in emerging markets (BRICS) from 2016 to 2022, resulting in 6278 observations. In a similar vein, Baldini et al. (2016) relied on panel regression with fixed effects to identify the characteristics at the country level that influence ESG disclosure practices using a sample of 14,174 firm year observations spanning 2005–2012. In their study, the impact was determined to be heterogeneous, as they can either decrease or increase disclosure levels, and may differ by ESG pillars. In comparison, another strand of literature focuses on ESG's impact on corporate performance and business outcomes. For example, claiming that companies benefit from the disclosure of ESG data by improving their brand reputation, Chen et al. (2023) determined that the impact of ESG ratings on the performance of large companies is statistically significant, while it is not significant for smaller firms. In addition, the results showed that ESG ratings have a stronger positive effect on corporate financial performance in high-risk cases compared to low-risk ones. This evidence was determined using a sample of 3332 listed companies around the world over a period of 2011–2020. In comparison, other studies investigated other aspects of this interrelation. For example, Kim and Meivitawanli (2023) used panel regression to determine factors that influence company governance scores, particularly focusing on board characteristics, while corporate social performance was the main focus in the study of Crespi and Migliavacca (2020).

2.2.2 Data envelopment analysis (DEA)

Compared to regression analysis, DEA has some benefits. As has been highlighted by Shewell and Migiro (2016), DEA offers advantages by identifying efficient performers in a given sample, enabling benchmarking against top performers. In contrast, parametric methods like regression analysis typically produce a comparator that reflects the average performance within a given population, thereby enabling measurement solely against this average. However, there is a relatively small body of literature that presents the use of DEA for ESG analysis. For example, the recent study of Cheng et al. (2023) employed a DEA approach to investigate the allocation of ESG efficiency and their connections with financial performance. By analysing MSCI ESG data from 2015 to 2019 on 1,108 Chinese companies, it was concluded that the most effective strategy involves enhancing overall ESG performance by improving environmental and social aspects while potentially sacrificing governance. The second finding identified a positive correlation between proportional efficiency and financial performance, whereas the connection between pillar mix efficiency and financial performance is more varied. In the same vein, Iazzolino et al. (2023) aimed to investigate whether ESG factors influence the financial efficiency of a selection of firms across various European sectors by means of a DEA approach. Results revealed differing impacts of ESG factors on firm efficiency across eight sectors, with some sectors, such as Energy and Materials, demonstrating greater sensitivity to ESG factors. Similarly, in the study of Pham et al. (2022), DEA was used to evaluate the business performance in the transportation industry by analysing a sample of 56 companies operating in the USA and China in 2019. It was determined that 13 companies were efficient, having the Constant Return to Scale (CRS). For inefficient ones, adjustments required in the scale of inputs and outputs to achieve efficiency were outlined. Then, Ordinary Least Squares (OLS) regression was used to describe the business performance in terms of ESG pillars, namely E, S, and G, together with the company's age, size, and leverage. It was determined that the scores of pillars E and S positively affect business performance. This paper is the example of two-stage network DEA, being an extension of conventional DEA methodology, which allows for a more comprehensive analysis of efficiency by dividing the units under consideration into two separate stages or processes. In this context, the network DEA, which assumes the first stage to have a "dominant" role, while the second stage to be a complementary "follower" role, was used to rank the corporate efficiency within network-based assessment (Phung et al. 2024). The authors proposed a technical efficiency evaluation network model under ESG-oriented, with the business operation assessed in one stage and market operation estimated in the other stage. Similarly, two-stage network DEA was employed in the study of Kao et al. (2022) to classify the production performance of companies in the Global Airline industry based on their energy and wealth-generation efficiencies. Here, ESG scores were used to define the proxy variables of company social responsibility (CSR) from different perspectives. Two-stage network DEA was also used in the paper of Moskovics et al. (2024) to determine a cause-effect relationship between ESG proxies and efficiency of the Brazilian listed companies. Their empirical findings suggest that market structures play a crucial role in determining both ESG scores and their efficiency. As for example, the second stage may be used to regress the efficiency estimates on some variables representing the considered units. As the efficiency score ranges between 0 and 1, the censored regression, namely Tobit model, could be constructed in the second stage. The combination of DEA and Tobit regression was applied for different purposes, such as, but not limited, assessing the efficiency and influencing factors for water resource system (Liang et al. 2021), for banks (Istaiteyeh et al. 2024), for building construction sites (Albertini et al. 2021), for rural primary health care centers (Mohammadpour et al. 2020).

In DEA, second-stage regression methods such as Tobit and OLS are commonly used to examine the relationship between efficiency scores and environmental variables (McDonald 2009; da Silva et al. 2019). However, Simar and Wilson (2007) have highlighted that such approaches can introduce bias, as environmental variables may be correlated with inputs and outputs used in the first-stage DEA model. Despite the lack of consensus on the optimal second-stage methodology, these analyses remain valuable for policymakers and regulators, providing insights into how external factors influence efficiency (da Silva et al. 2019). In our study, we employ Tobit regression, considering that the composite indicator derived from the BoD model is a weighted sum of indicators, ranging between 0 and 1.

To handle the desirable and undesirable performance indicators, Ben Lahouel et al. (2022) specify a composite indicator to assess the social and environmental (socio-environmental) performance of airline firms over time using the BoD model based on the directional distance function. Specifically, the BoD model uses the directional distance function to handle the desirable and undesirable socio-environmental performance indicators. The composite indicator achieved on this model is used to measure the socio-environmental performance over time by applying the Malmquist productivity index which enables capturing the efficiency change and a technical change components over time.

2.2.3 Other methods

In addition to panel regression and DEA, other methodologies have been used to investigate the relation between ESG factors and corporate performance. For example, in the study of Teplova et al. (2023) a neural network and Shapley values were used to reveal the impact of different ESG indicators on stock liquidity in the Russian market. Six machine learning approaches were used to forecast the ESG rating of companies using firm-specific and macroeconomic predictors in the research (Chowdhury et al. 2023). ESG rating was also analyzed by Gospodarowicz et al. (2024) using financial, spatial and systemic importance variables observed for banks employing a multinomial ordered logit model. In order to assess the impact of a particular event, the difference-in-differences (DID) model was used in the study of Zhang et al. (2024). Using this model, the authors analyzed the influence of green finance policy on the practices of ESG disclosure among Chinese listed firms. Their findings are useful for policy makers because they provide a better understanding of the economic implications of the policies introduced. The same approach was used in the research of Tian et al. (2024), where it was shown that the implementation of a carbon emission trading scheme can remarkably improve ESG performance, with green technology innovation, analyst attention and agency cost acting as a partial intermediary.

3 Methodology

3.1 Data

The study uses annual observations of 559 manufacturing companies operating in Europe (see Table 1), Asia and Oceania (see Table 2) regions. Among them, 474 companies were functioning in the developed countries. The companies were selected based on the availability of data on the platform of Eikon (2023), covering the period 2016 to 2019. Thomson Reuters ESG Scores, which assess a company’s sustainability performance across ten categories based on publicly reported information (Eikon 2017), were collected from Thomson Reuters databases. Accordingly, financial data were retrieved from the Orbis database. More specifically, the environmental pillar (E) covers categories such as resource use, emissions, and innovation; the social pillar (S) includes workforce, human rights, community, and product responsibility; and the governance pillar (G) covers management, shareholders, and corporate social responsibility strategy. Each pillar includes a varying number of

Table 1 Counts of companies in Europe

Country	Austria	Belgium	Switzerland	Germany	Denmark	Spain	Finland	France	United Kingdom	Ireland	Italy	Netherlands	Norway	Sweden
Code	AUT	BEL	CHE	DEU	DNK	ESP	FIN	FRA	GBR	IRL	ITA	NLD	NOR	SWE
No.	5	7	27	43	12	7	13	29	50	5	4	9	3	16

Table 2 Counts of companies in Asia and Oceania

Country	Australia	China	Indonesia	India	Israel	Japan	New Zealand	Philippines	Saudi Arabia	Singapore	Turkey
Code	AUS	CHN	IDN	IND	ISR	JPN	NZL	PHL	SAU	SGP	TUR
No.	23	28	5	37	4	216	1	3	2	1	9

measures, totaling over 400 altogether. In order to generate an almost flat distribution of the scores, a percentile rank scoring methodology is adopted.

To generalize the data description, define the variables by $\left(X_{jt}, Y_{jt}, Z_j\right)$, where X_{jt} denotes the key performance indicators of the company j for the period t, $Y_{jt} = (E_{jt}, S_{jt}, G_{jt})$ denotes the environmental (E), social (S) and governance (G) scores of the company j in the period t, Z_j represents additional information such as industry (I), country (C) and region (R) for each company, $j = 1, \dots, n$, and the time index is given by $t = 1, \dots, T$. The key performance indicators of the company X_{jt} were selected to represent the dimensions of financial performance and innovation aspects based on published studies (Makri and Scandura 2010; Custódio and Metzger 2014; Fernández-Sastre and Montalvo-Quizhpi 2019; Huang et al. 2023). More specifically, the financial performance of companies has a significant influence on their environmental results, as profits empower the development of innovative solutions that mitigate environmental pollution, and increased capital expands the possibilities for such innovations. Positive financial results, when channeled into research and experimental development expenses, have a more pronounced impact on reducing environmental pollution. All indicators represented by X_{jt} are summarised in Table 3.

3.2 Two-stage DEA model

3.2.1 Data envelopment analysis

Initially introduced by Charnes et al. (1978), DEA is a non-parametric method that enables us to assess the relative efficiency of a homogeneous set of individual decision making units (DMU) that use multiple inputs to produce multiple outputs. DEA measures the relative efficiency of a given DMU (j_0) against the frontier of best practices defined by the linear combination of peers, considered as the benchmarks. These units are efficient, as they achieved an efficiency score equal to 1 (or 100 %), while the DMUs outside the frontier are inefficient and have an efficiency score less than one. The conceptual idea of DEA is to determine the efficiency e_{j_0} of

Table 3 Company performance indicators X_{jt} used in the analysis

Group	Name	Notation	Formula
Financial performance	Company size	*SIZE*	Log(assets)
	Return on assets	*ROA*	Net-income/assets
	Profitability	*PROFITABILITY*	Sales/net-income
	Leverage	*LEVERAGE*	(Long-term debt + short-term debt)/assets
	Tobin q	*TOBINQ*	(Market capitalization*1000 + assets − common equity)/assets
Innovation performance	Research and development expenditures	*R & D*	R & D expenditures/assets

each DMU$_{j_0}$ by maximizing the ratio of the weighted outputs to the weighted inputs, through the selection of weights obtained by comparing it with the best levels of inputs and outputs observed on the frontier of best practices. Based on the comparison with peers, the DEA allows us to determine the input and output targets for inefficient companies.

For a given period t, considering that n companies j ($j = 1, \ldots, n$) use s inputs x_{kj} ($k = 1, \ldots, s$) to produce m outputs y_{ij} ($i = 1, \ldots, m$), the input weights v_k and the output weights w_i are determined by the input oriented DEA model (Charnes et al. 1978), assuming constant returns to scale, given by

$$\begin{aligned}
&Max \;\; \mathrm{e}_{j_0} = \sum_{i=1}^{m} w_i y_{ij_0} \\
&\boldsymbol{s.t.} \quad \sum_{i=1}^{m} w_i y_{ij} - \sum_{k=1}^{s} v_k x_{kj} \le 0 \qquad \forall j = 1, \ldots, n \\
&\qquad \sum_{k=1}^{s} v_k x_{kj_0} = 1 \\
&\qquad w_i, v_k \ge 0 \qquad \forall i = 1, \ldots, m; \qquad k = 1, \ldots, s.
\end{aligned} \tag{1}$$

For each DMU$_{j_0}$ under evaluation, model (1) maximizes the efficiency score, e_{j_0} given by the total virtual output of ($\sum_{i=1}^{m} w_i y_{ij_0}$) for each virtual input ($\sum_{k=1}^{s} v_k x_{kj_0}$) used, determining the weights w_i and v_k. Thus, the weights are obtained endogenously by the DEA model and individually calculated for each company under analysis DMU$_{j_0}$, avoiding prior fixed weights. If companies were evaluated through m output indicators (Y_{ij}) without explicitly referring to the resources used, it is possible to adapt the model (1) to calculate the performance score (Melyn et al. 1991) for each company by setting an identical input level for all companies, which for simplicity was assumed to be equal to one as in Knox Lovell (1995). Thus, Y_{ij} is the value of the indicator i for the company j ($j = 1, \ldots, m$), in a given period t, and w_i is the weight attributed to the indicator i. For each company under evaluation, model (2) selects the w_i for each indicator Y_{ij_0} that maximizes its CI_{j_0} score. This is the BoD model proposed by Cherchye et al. (2007):

$$\begin{aligned}
&CI_{j_0} = \max \sum_{i=1}^{m} w_i Y_{ij_0} \\
&\boldsymbol{s.t.} \quad \sum_{i=1}^{m} w_i Y_{ij} \le 1 \qquad \forall j = 1, \ldots, n \\
&\qquad w_i \ge 0 \qquad \forall i = 1, \ldots, m.
\end{aligned} \tag{2}$$

In the present study, the output indicators Y_{ij} include the environmental indicators of the company (E_{jt}), social (S_{jt}), and governance (G_{jt}), for each period t, in which CI_{j_o} is considered the sustainability performance of the company j_o in period t, measured against the frontier of best practice observed in period t. For each assessment, it is necessary to avoid having a null weight attributed to any indicator, as it would be translated as a null contribution to sustainability performance CI_{j_o}. Since the relative importance of each indicator to calculate CI_{j_o} is measured as a percentage, the proportional virtual weight restrictions are applied to the average company (Zanella et al. 2013) and imposed on the model (2). That company is an artificial DMU whose outputs are the average of environmental (E_{jt}), social (S_{jt}), and governance (G_{jt}) indicators. Thus, constraint (3) added to model (2) means that the optimum solution of w_i assigned to each indicator i ($i = 1, \ldots, m$) should range between a minimum contribution percentage (α) and a maximum contribution percentage β in the average company, given by

$$\alpha \leq \frac{w_i(\sum_{j=1}^{n} Y_{ij}/n)}{\sum_{i=1}^{m} w_i(\sum_{j=1}^{n} Y_{ij}/n)} \leq \beta \qquad \forall i = 1, ..., m. \tag{3}$$

This implies that all companies are evaluated relative to a unique best practice frontier since weight restrictions are uniform for all companies. This is a way to incorporate judgment about the proportion in which the corresponding outputs should contribute to performance (Wong and Beasley 1990). The implementation of weight restrictions (3) should strike a balance between flexibility and consistency. Unrestricted DEA offers the highest level of flexibility, while ensuring suitable consistency requires accounting for all dimensions (company environmental, social, and governance indicators). In order to strike a balance between flexibility and consistency, we set $\alpha = 0.015$ and $\beta = 0.97$, allowing each company the freedom to choose weights that maximize its performance while adhering to constraint (3), thus preventing null weights. Since these bounds are imposed on the virtual outputs of the average DMU, they maintain the symmetry of the model for all companies, since each unit is assessed on the same feasible region (Dyson et al. 2001). Thus, the model (2) with weights imposed by (3), with $\alpha = 0.015$ and $\beta = 0.97$, is hereafter named BoDw.

It is also important to apply benchmarking to identify peers for each company evaluated and to find their best practices. The peer analysis is an important by-product of the DEA evaluation, which is obtained through the dual formulation of the BoDw model (Cooper et al. 2006).

3.2.2 Tobit regression

To explore the effect of explanatory variables given by X_{jt} on sustainability performance, a Tobit regression model (Wang 2019; Martins et al. 2021) could be used since the performance score given by the DEA model (see, Eq. 2) ranges between 0 and 1 (Hoff 2007). As such, a Tobit regression model is given by Eq. (4):

$$\begin{aligned} CI_{jt} = {} & \beta_0 + \beta_1 SIZE_{jt} + \beta_2 ROA_{jt} + \beta_3 PROFITABILITY_{jt} + \beta_4 LEVERAGE_{jt} + \\ & + \beta_5 TOBINQ_{jt} + \beta_6 R\&D_{jt} + \mu_t + v_j + \epsilon_{jt}, \end{aligned} \tag{4}$$

where the dependent variable, CI_{jt}, corresponds to the sustainability performance performance score for each company j, for a given year t, β_0 is the intercept, β_l ($l = 1, ..., 6$) is the coefficient to be estimated for each observed explanatory variable X_{jt}, μ_t is a dummy variable for each year, and ϵ_{jt} are the residuals which are independent and identically (i.i.d.) normally distributed, $N(0, \sigma^2_\epsilon)$. A likelihood ratio test was used to compare the pooled estimator with the panel estimator. In this case, the null hypothesis that there are no panel-level effects was rejected. Thus, the random effects model (4) was used, where the random effects, ν_j, are i.i.d. $N(0, \sigma^2_\nu)$, and ϵ_{jt} are independent of ν_j, i.e.

Globally, in the first stage, sustainability performance CI_{jt} is assessed for each company j for a given year t and measured against the best practice frontier observed in all periods t ($t = 1, \dots, n$) using the BoDw model, considering the indicators Y_{tj}, which correspond to the environmental pillars of the company (E_{jt}), social (S_{jt}) and governance (G_{jt}). In the second stage, the Tobit regression model (4) is used to explore the effect of the explanatory variables, X_{jt}, on the composite sustainability performance score, CI_{jt}.

The methodology was conducted using R software. Specifically, the LSolve and cenReg packages were used for estimation, while the Benefit of the Doubt model was implemented with the lpSolve package. Additionally, the Tobit model was estimated using the cenReg package, employing the Berndt-Hall-Hall-Hausman (BHHH) optimization method.

4 Results

4.1 Data exploratory

To summarize the data, the ESG pillar scores observed for the companies considered were averaged by country, while each country is represented by the companies operating there (see Fig. 2). When comparing the scores of the ESG pillars among

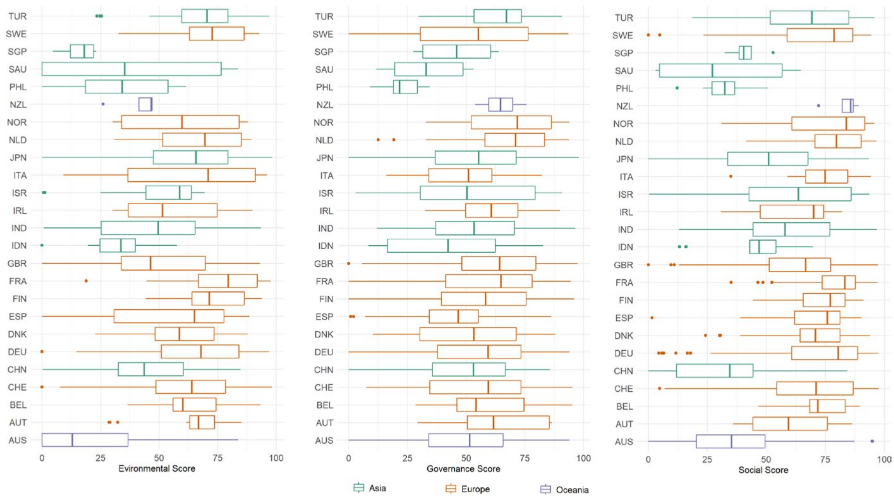


Fig. 2 Scores of E, S, and G pillars observed in the selected countries

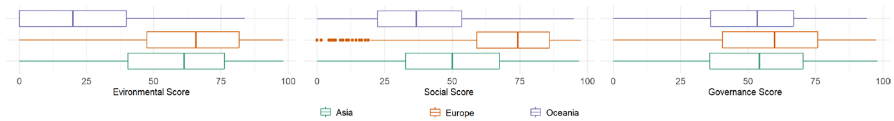


Fig. 3 Scores of E, S, and G pillars observed in the considered regions

themselves, one can observe that the governance score and its variability are quite similar across all countries. Meanwhile, environmental and social scores are either relatively high or, conversely, quite low. Moreover, their distributions of values are either very concentrated or very dispersed. In particular, the distribution of social scores tends to be asymmetric, possibly reflecting the varying emphasis companies place on social responsibility, unlike the more consistent practice observed with government scores.

Figure 3 displays the ESG pillar scores averaged for each region considered. We may infer that the governance score shows very little variation between regions, which is not true for other scores. In particular, the social score tends to vary across the regions under consideration, whereas the distribution of the environment score is quite similar between Europe and Asia, but differs in Oceania.

Figure 4 shows the distribution of the ESG pillar scores summarized by development level. In particular, developed countries demonstrated better sustainability performance, with the largest differences observed for the environmental score, while the smallest gap is determined for the governance score. Surprisingly, the spread of values is consistent across the ESG pillars, regardless of the level of a country's development.

Figure 4 shows the ESG scores for manufacturing companies over a period between 2016 and 2019. It could be seen that there was significant progress in the sustainability efforts of these companies, particularly in environmental protection and social responsibility, as indicated by the notable increase in these scores. This improvement can be attributed to substantial investments in environmental innovations and the intensified implementation of social responsibility projects by manufacturing companies during this period. Innovations in energy efficiency designed to reduce energy consumption and greenhouse gas emissions in production processes have been rapidly adopted. This included energy-efficient equipment, lighting systems, advances in heating, ventilation, and air conditioning systems, as well as the integration of renewable energy sources (solar, wind, and geothermal energy) into the production process. Companies donated more funds, resources, and products to support charities, community development projects, disaster relief, educational institutions, health care facilities, and cultural initiatives. The progress of the governance score in the business of manufacturing companies was more moderate. During this period, the principles of ethical and honest business practices began to be discussed and implemented more actively. In addition, there was a more active effort to reorganize company boards by redistributing quota between men and women. Despite significant improvements in environmental and social scores, these scores still only exceed 60, while the target value is 80 and above. Meanwhile, the governance score

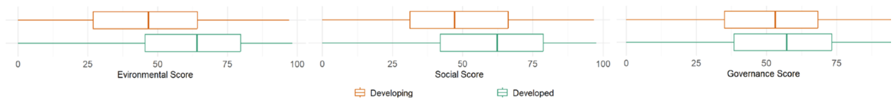


Fig. 4 Scores of E, S, and G pillars based on the country's development level

Fig. 5 Scores of E, S, and G pillars observed for the manufacturing companies by year

lagged behind the environmental and social scores. This indicates that achieving sustainability in company activities continues to be a challenging issue (Fig. 5).

The descriptive statistics by year is given in Table 4. The mean, standard deviation, minimum, maximum values, quartiles, and median of financial and ESG indicators of manufacturing companies were calculated by year.

Table 4 shows that on average the sustainability scores of the companies considered improved each year. Among all financial indicators computed for the companies analyzed, the most stable over time on average were *SIZE*, *LEVERAGE*, *ROA*, and *R & D*. Indicators such as *TOBINQ* and particularly *PROFITABILITY* have changed considerably without a clear trend over time.

4.2 Results of DEA

4.2.1 Sustainable performance assessment each year

The BoDw model was used to evaluate the sustainability performance of each company for each year t, using the environmental (E_{jt}), social (S_{jt}), and governance (G_{jt}) pillars as indicators, with the best-practices frontier for the period t defined by benchmark companies, which have an efficiency score equal to 1, in that year. Furthermore, the BoD model (2) is used as a baseline model.

Table 4 Descriptive statistics

	Year	Mean	Std. dev.	Min.	0.25	Median	0.75	Max.
SIZE	2016	15.47	1.80	0.00	14.66	15.51	16.43	19.86
	2017	15.54	2.04	0.00	14.76	15.61	16.56	20.02
	2018	15.52	2.25	0.00	14.81	15.66	16.59	20.05
	2019	15.53	2.36	0.00	14.81	15.70	16.65	20.09
LEVERAGE	2016	0.20	0.15	0.00	0.08	0.20	0.30	1.15
	2017	0.20	0.14	0.00	0.09	0.19	0.29	0.91
	2018	0.20	0.14	0.00	0.09	0.19	0.29	1.08
	2019	0.21	0.15	0.00	0.10	0.20	0.31	1.30
TOBINQ	2016	1.88	1.47	0.00	1.11	1.43	2.06	15.58
	2017	2.07	1.77	0.00	1.18	1.56	2.28	19.62
	2018	1.77	1.74	0.00	0.99	1.27	1.92	23.02
	2019	1.90	1.96	0.00	1.03	1.30	2.06	23.37
ROA	2016	0.04	0.15	−2.09	0.02	0.05	0.07	0.40
	2017	0.05	0.11	−1.30	0.03	0.05	0.08	0.38
	2018	0.04	0.19	−3.89	0.03	0.05	0.08	0.36
	2019	0.04	0.12	−1.85	0.02	0.04	0.07	0.33
PROFITABILITY	2016	28.89	198.21	−2768.31	7.59	14.54	25.77	2232.59
	2017	17.74	65.22	−1126.45	7.43	13.57	22.72	581.51
	2018	16.58	46.86	−733.35	7.57	13.35	21.81	463.57
	2019	31.63	224.97	−558.37	6.51	12.24	22.49	3742.33
R & D	2016	0.03	0.07	0.00	0.01	0.02	0.04	1.45
	2017	0.03	0.05	0.00	0.01	0.02	0.04	0.85
	2018	0.03	0.05	0.00	0.01	0.02	0.04	0.69
	2019	0.03	0.05	0.00	0.01	0.02	0.04	0.71
E	2016	53.75	25.73	0.00	36.95	55.76	74.71	97.71
	2017	56.48	25.12	0.00	40.21	60.72	76.42	98.16
	2018	58.82	24.91	0.00	43.20	63.83	79.19	98.25
	2019	61.22	24.51	0.00	46.41	65.73	81.02	97.59
S	2016	52.88	25.38	0.00	33.75	54.31	73.98	97.28
	2017	56.74	24.73	0.00	40.15	59.63	76.75	97.19
	2018	58.59	24.39	0.00	41.78	62.35	78.52	97.19
	2019	60.85	23.96	0.00	45.61	66.03	79.33	97.62
G	2016	52.39	22.52	0.00	35.73	54.51	69.53	96.46
	2017	52.53	22.76	0.00	35.53	54.16	70.14	96.70
	2018	55.56	22.96	0.00	38.57	58.55	73.30	97.93
	2019	57.03	23.22	0.00	41.70	59.15	75.61	95.98

For each year $t = t_1, ..., T$ that corresponds to 2016, 2017, 2018, and 2019, respectively, Table 5 summarizes the results of the BoD and BoDw models in terms of average value of CI ($\overline{CI}$), standard deviation (SD), number of companies

Table 5 Performance assessment for each year using BoD and BoDw models

Year	2016		2017		2018		2019	
Model	BoD	BoDw	BoD	BoDw	BoD	BoDw	BoD	BoDw
Asia								
$\overline{CI}$	0.67	0.66	0.68	0.68	0.70	0.69	0.72	0.72
SD	0.21	0.21	0.20	0.20	0.19	0.19	0.19	0.19
N	305	305	305	305	305	305	305	305
No. of benchmarks	3	3	2	2	2	1	3	3
Europe								
$\overline{CI}$	0.77	0.77	0.78	0.78	0.80	0.79	0.82	0.81
SD	0.18	0.18	0.17	0.17	0.17	0.17	0.16	0.16
N	230	230	230	230	230	230	230	230
No. of benchmarks	9	8	6	6	7	7	7	6
Oceania								
$\overline{CI}$	0.63	0.62	0.61	0.60	0.60	0.60	0.61	0.60
SD	0.20	0.20	0.20	0.20	0.21	0.21	0.23	0.23
N	24	24	24	24	24	24	24	24
No. of benchmarks	0	0	0	0	0	0	0	0
Developed								
$\overline{CI}$	0.72	0.72	0.74	0.73	0.75	0.74	0.77	0.77
SD	0.20	0.20	0.19	0.19	0.19	0.19	0.18	0.19
N	474	474	474	474	474	474	474	474
No. of benchmarks	11	10	7	7	9	8	9	8
Developing								
$\overline{CI}$	0.61	0.61	0.64	0.63	0.66	0.65	0.69	0.68
SD	0.22	0.22	0.22	0.22	0.19	0.19	0.19	0.19
N	85	85	85	85	85	85	85	85
No. of benchmarks	1	1	1	1	0	0	1	1
All								
$\overline{CI}$	0.71	0.70	0.72	0.72	0.73	0.73	0.76	0.75
SD	0.21	0.21	0.20	0.20	0.19	0.19	0.19	0.19
N	559	559	559	559	559	559	559	559
No. of benchmarks	12	11	8	8	9	8	10	9

evaluated (N), and number of benchmark companies observed in all companies and for each group, in which the region or development level is considered.

The comparison between the BoDw and BoD models enables us to observe slight differences in the results of CI. For example, $\overline{CI}$ is almost the same, and the number of benchmarks only decreases by a maximum of one unit, except in 2017, when weight restrictions are imposed on the BoD model. Despite this, the more significant differences are related to the weight values that vary greatly due to the great flexibility of the BoD model, in which at least 86% of the companies are assessed with null weights for at least one pillar. To ensure that these pillars are not zero in performance evaluation, the BoDw model should be used, in which constraint (3) imposes that the minimum weight assigned to each pillar for the assessed unit must be at least 1.5% (and at a maximum of 97%) when applied to the average company observed. This lower limit is imposed to give high flexibility to the model, avoiding null weights in the evaluation. In the following, the evaluation of the sustainability performance for each year is analyzed with the results of the BoDw model.

Globally, the $\overline{CI}$ of the BoDw model ranges between 0.70 in 2016 and 0.75 in 2019, indicating that the homogeneity of sustainability performance increases slightly in this period. This suggests that on average, inefficient companies are getting closer to efficient companies between 2016 and 2019. This is also reflected in the number of benchmark companies for each year, which ranges between the minimum of 8 units in 2017 and 2018, and a maximum of 11 units in 2016, which are 9 units in 2019.

Concerning the dominant benchmarks, there were one Japanese and three Swiss companies that remained on the frontier throughout the period. There was a German company that was efficient throughout the period except 2017. There was a British company that was efficient in the last three years and a French company that was efficient in all years except in 2018. A Turkish company and another company from Finland were determined as benchmarks twice, that is, in 2016 and 2019, and 2016 and 2017, respectively. The remaining companies were observed as benchmarks for only one year. Among them, French, Japanese, and Dutch companies were identified in 2016, an Indian company—in 2017, a French and a British company—during 2018, and a Japanese company – in 2019. The profile of the benchmarks is given in Fig. 6, which presents the average of the pillars for the benchmarks and the underperforming companies for each year.

Thoroughly, the average of each pillar has increased for benchmarks and underperforming companies. For the benchmarks, pillar E increases from 91 to 95 with a slight decrease to 89 in 2017, pillar G increases from 82 to 86 (a slight decrease in 2019), pillar S has been increased over the years from 90 to 93 (a slight decrease in 2019). For underperforming companies, pillar E increases from 53 to 61, pillar G increases from 52 to 57, and pillar S has increased over the years from 52 to 60. We may infer that, on average, underperforming companies have slightly improved their practices for all pillars following the benchmarks. Meanwhile, the benchmarks had more difficulties in maintaining sustainable practices, mainly in pillars G and S.

Each company should undergo benchmarking, where every inefficient company learns the best practices from their benchmarks or peers. To exemplify, the Austrian company ID4 is evaluated with $CI = 0.705$ in 2019. This company should learn the best practices from its peers, which are the companies ID109 (from Germany) and ID493 (from Japan), which have the intensity variables (λ) equal to 48% and 52%, respectively. Thus, possible efficient targets for each pillar correspond to the linear combination of the values observed in the peers. In

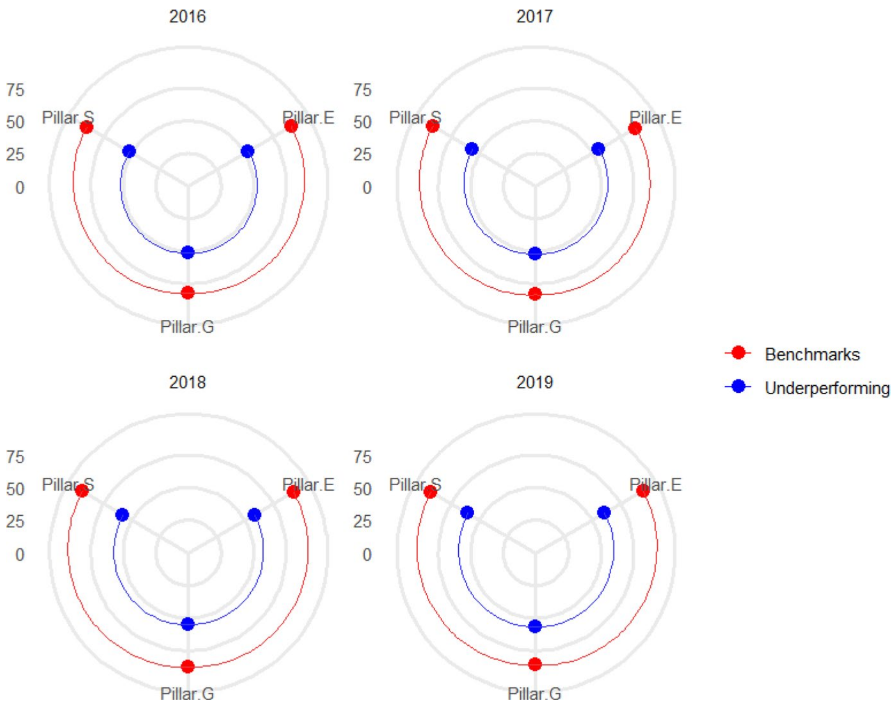
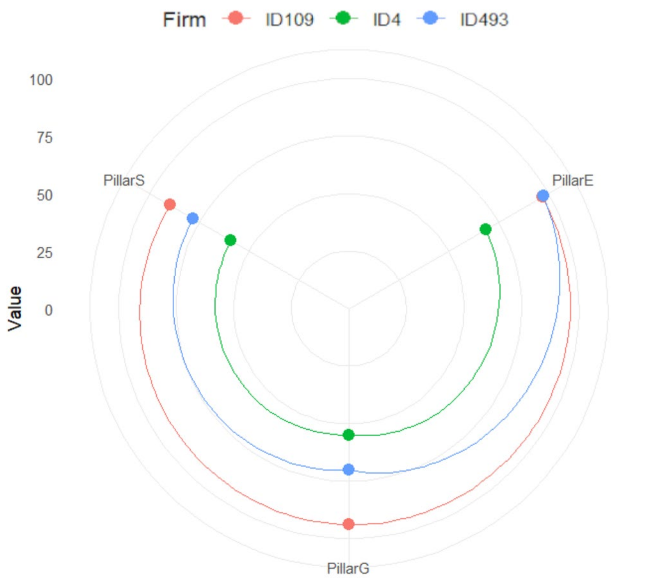


Fig. 6 Average profile of benchmarks and underperforming companies

Fig. 7, it is possible to see the observed value and target of each ESG pillar for company ID4 and its peers ID109 and ID493.

The heterogeneity of the sustainability performance of companies in successive years is compared using the approach proposed by Vaz and Camanho (2012). Statistical tests on DEA results applied to various groups have been also used in Bogetoft and Otto (2011). The Kolmogorov-Smirnov (KS) test is used to assess whether two independent samples concerning successive years are from populations with the same distribution. Thus, the KS test compares the independent samples of *CI* in years 2016 and 2017 ($p.value = 0.4846$), 2017 and 2018 ($p.value = 0.4846$), 2018 and 2019 ($p.value = 0.1143$). It is possible to conclude that no statistical differences are observed between the successive frontiers, which means that the level of heterogeneity is similar between them. Furthermore, the *p.value* of the Mann Whitney U (MW test), also known as the Wilcoxon rank-sum test, indicates that no differences are observed in the medians between 2016 and 2017 ($p.value = 0.2339$); 2017 and 2018 ($p.value = 0.3409$), but a statistical difference is detected between 2018 and 2019 ($p.value = 0.01369$). This implies that in the first three years the level of heterogeneity among companies observed in successive years is similar, although the median of the performance is significantly higher in 2019 than in the previous year. This indicated that the inefficient companies in 2019 tend to be closer to the frontier than in 2018, increasing the homogeneity level among companies.



Pillar (%)	ID4		Peers	
			ID109	ID493
	Observed	Targets	$\lambda = 0.48$	$\lambda = 0.52$
E	68.64	97.30	96.98	97.59
S	59.16	83.85	89.79	78.35
G	54.8	81.61	93.99	70.15

Fig. 7 Benchmarks of the company ID4

Given the asymmetry of the distribution of *CI* observed in each year, the Kruskal-Wallis (KW) test is used in each year (in which the frontier is the same) to compare the equality of the medians among at least two groups. Thus, the KW test was applied to compare the performance among the three regions, Asia, Europe, and Oceania, in each year. In addition, the MW test is used to compare performance medians between developed and developing countries and each pair of regions. Significant differences in performance levels are found among regions ($p.value < 0.001$ for the KW test, in each year). MW tests indicate that the median is higher in European countries than in other regions ($p.value < 0.001$ for each year). This implies that higher ESG scores were observed in the European region. In addition, the performance level is consistently higher for developed countries compared to developing countries ($p.value < 0.001$ for the MW test, in each year).

During 2016 and 2019, the behavior of individual companies in each country can be seen in Fig. 8. For instance, the performance of companies in Belgium and France remains consistently good over time. In contrast, the performance of companies in Austria, Japan, Germany, and the United Kingdom was found to be more heterogeneous, ranging from highly efficient to less efficient.

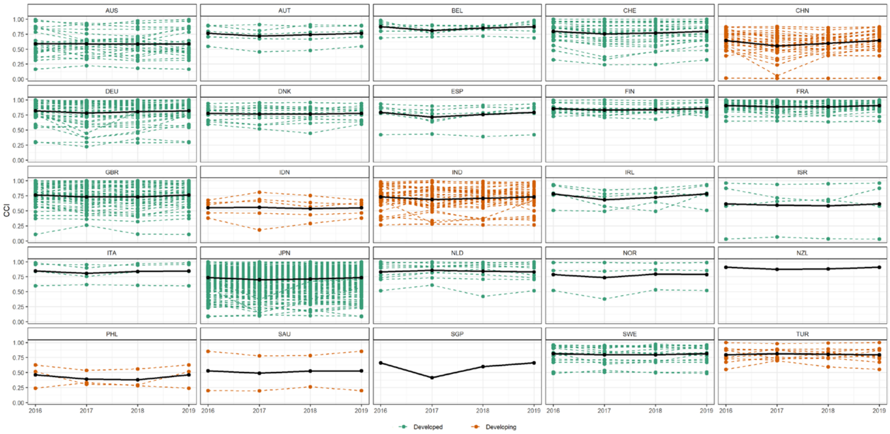


Fig. 8 Average of *CI* by country and year

4.2.2 Exploring the determinants of sustainability performance

This section explores the determinants of sustainability performance given by the composite indicator *CI* that aggregates the three sustainability pillars E, S, and G. In this study, potential determinants represent the financial performance of manufacturing companies.

To ensure that all companies are evaluated against the same reference frontier in order to obtain a comparable performance score, the sustainability performance of each company j, CI_{jt}, is evaluated by the BoDw model, considering the pooled frontier that includes the best practices of companies observed in all years $t = 2016, \ldots, 2019$, using the pillars of environmental (E_{jt}), social (S_{jt}), and governance (G_{jt}) indicators.

The statistics of financial indicators (X_{jt}) for the determined benchmarks ($CI = 1$) and inefficient companies ($CI < 1$) are given in Table 6. It could be seen that benchmarks tend to have higher levels of expenditure *LEVERAGE*, *R & D*, *ROA*, *TOBINQ*, and *SIZE* than inefficient companies, while *PROFITABILITY* is on average higher for inefficient companies, with a much larger deviation.

Table 6 Statistics of financial data of benchmarks ($CI = 1$) and inefficient companies, using the pooled frontier

Financial data	$CI = 1$		$CI < 1$	
	$\overline{CI}$	*SD*	$\overline{CI}$	*SD*
LEVERAGE	0.29	0.12	0.20	0.15
PROFITABILITY	12.80	11.08	23.73	155.55
R & D expenditure	0.07	0.06	0.03	0.06
ROA	0.09	0.07	0.04	0.15
TOBINQ	2.14	0.82	1.91	1.75
SIZE	17.25	1.09	15.51	2.12

Table 7 Panel Tobit results

Variable	Estimate	Std. Error	t statistic	*p.value*	
(Intercept)	0.3213	0.0099	32.5370	0.0000	***
LEVERAGE	0.1098	0.0120	9.1780	0.0000	***
PROFITABILITY	−0.0000	0.0000	−0.8680	0.3857	
R & D expenditure	0.0159	0.0497	0.3210	0.7480	
ROA	0.0513	0.0200	2.5710	0.0101	*
TOBINQ	0.0007	0.0016	0.4680	0.6396	
SIZE	0.0196	0.0006	32.5770	0.0000	***
Factor(RegionName)=Europe	0.1100	0.0042	26.0100	0.0000	***
Factor(RegionName)=Oceania	0.0084	0.0108	0.7770	0.4372	
Factor(Development)=Developing	− 0.0737	0.0056	−13.1180	0.0000	***
Factor(year)=2017	0.0162	0.0057	2.8370	0.0046	**
Factor(year)=2018	0.0347	0.0050	6.9100	0.0000	***
Factor(year)=2019	0.0525	0.0043	12.1380	0.0000	***
Log(σ_μ)	− 2.0160	0.0108	− 187.6040	0.0000	***
Log(σ_ν)	− 2.6250	0.0105	− 250.8540	0.0000	***

Significance codes: ‘.’ 0.1, ‘*’ 0.05, ‘**’ 0.01, ‘***’ 0.001

df=15, logLik=1918.377, AIC = −3806.75, n = 559

To identify the effect of the explanatory variables, X_{jt}, on the sustainability performance, CI_{jt} score, the Tobit regression model (4) for panel data with random effects was used. The results are summarised in Table 7.

In fact, all financial indicators have a global positive effect on the sustainability performance of companies. However, only the leverage, ROA, and company size have a statistically significant impact on the sustainability performance. Furthermore, according to the Tobit regression, European companies exhibit a statistically significantly higher performance ($p.value < 0.001$) compared to companies located in Asia. In addition, the results also reveal that developing countries have a statistically significantly lower performance ($p.value < 0.001$) than developed countries. The results indicate that companies exhibited significantly better performance in 2017, 2018, and 2019 compared to the reference year 2016. Furthermore, the increasing trend observed over these years suggests a growing effort by companies toward sustainability in ESG pillars.

5 Conclusion

In the literature, sustainability is often explored in terms of ESG score, rating, or disclosure. Researchers typically investigate the relationship between ESG and company financial performance from both perspectives: the impact of ESG on financial performance and vice versa. This study contributes to the field by using ESG pillar scores to assess companies’ efficiency in terms of sustainability performance, and subsequently examining the impact of financial indicators on this performance. To achieve this twofold goal, the two-stage DEA model was proposed in the study.

To demonstrate the use of a two-stage methodology to evaluate sustainability performance, a sample of 559 manufacturing companies operating between 2016 and 2019 was collected. In the first stage, the BoDw model was applied to assess the performance of companies using the best practice frontier for each year. This model enabled us to determine the optimal non-null weights to assign to each ESG pillar to aggregate them into the composite indicator *CI* that captures the sustainability performance for each company. In the second stage, the sustainability performance for each company j and year t is regressed on their performance indicators using the Tobit panel regression with random effects, to understand the drivers of the sustainability performance given by CI_{jt}. In this case, CI_{jt} is calculated against the pooled frontier defined by the best practices observed from 2016 and 2019, as the BoDw model includes environmental (E_{jt}), social (S_{jt}), and governance (G_{jt}) indicators for all companies observed throughout the period.

In the first stage, we can conclude that globally, the homogeneity of the sustainability performance of the companies increased during the period observed, in which the inefficient companies are getting closer to the best practice frontier. However, the best performance is observed in a few companies, specifically 1.6% of companies in 2019, which implies that companies have experienced difficulties in improving best practices towards the Green Deal, since there are one Japanese and three Swiss companies that stay on the frontier for the whole period and three companies (German, British, and French) that are on the frontier only for 3 years. This suggests that some policies might be needed to reinforce and sustain the position of companies worldwide.

The progress observed over the period is evident in the average score of each pillar, which has shown an increase for both benchmark and underperforming companies. Specifically, among benchmark companies, pillar E increased from 91 to 95, pillar G increased from 82 to 86, and pillar S increased from 90 to 93. This indicates that benchmarks of the manufacturing companies improved their ESG pillars, with Governance showing the most significant increase of at least 4.88%, while the smallest increase of 3.33% was observed in the Environmental pillar. This trend was also determined for underperforming companies, as on average pillars E, G, and S increased from 53, 52, 52 to 61, 57, and 60, respectively. In order to improve the sustainability performance, each inefficient company should learn the best practices of its benchmarks as explained previously for the company ID4. By emulating these practices, each inefficient company can improve its sustainability performance towards the efficient targets defined by the benchmarks.

The results from the second stage reveal that the top performers in sustainability exhibited higher values of *LEVERAGE*, *R & D* expenditure, *ROA*, *TOBINQ*, and *SIZE* compared to inefficient companies, while *PROFITABILITY* is generally higher for inefficient companies but with much greater variability, which means that the profitability levels of the companies vary greatly from one company to another, rather than clustering closely around the average profitability.

Future studies might consider broadening the range of indicators that describe overall company performance. Additionally, conducting a multi-sector comparison of sustainable performance and evaluating the influencing factors, similarities, or discrepancies among sectors would be valuable. Given that companies operate in various countries and climate zones, it would be beneficial for future research to extend the DEA model to include spatial analysis.

Author contributions The coauthors contributed equally to this work.

Funding This research has received funding from the Research Council of Lithuania (LMTLT), agreement No. S-PD-22-23. This work was also supported by national funds through FCT/MCTES (PIDDAC): CeDRI, UIDB/05757/2020 (DOI: 10.54499/UIDB/05757/2020) and UIDP/05757/2020 (DOI: 10.54499/UIDP/05757/2020); and SusTEC, LA/P/0007/2020 (DOI: 10.54499/LA/P/0007/2020).

Data availability Data used in this study were obtained from Orbis Database and Thomson Reuters Eikon Datastream.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Informed consent Not applicable.

Ethical approval Not applicable.

References

Abdi Y, Li X, Càmara-Turull X (2021) Exploring the impact of sustainability (ESG) disclosure on firm value and financial performance (FP) in airline industry: the moderating role of size and age. Environ Dev Sustain 24(4):5052–5079. https://doi.org/10.1007/s10668-021-01649-w

Abdul-Rashid SH, Sakundarini N, Raja Ghazilla RA, Thurasamy R (2017) The impact of sustainable manufacturing practices on sustainability performance: empirical evidence from Malaysia. Int J Oper Prod Manag 37(2):182–204. https://doi.org/10.1108/ijopm-04-2015-0223

Albertini F, Gomes LP, Grondona AEB, Caetano MO (2021) Assessment of environmental performance in building construction sites: data envelopment analysis and tobit model approach. J Build Eng 44:102994. https://doi.org/10.1016/j.jobe.2021.102994

Aljamal D, Salem A, Khanna N, Hegab H (2024) Towards sustainable manufacturing: a comprehensive analysis of circular economy key performance indicators in the manufacturing industry. Sustain Mater Technol. https://doi.org/10.1016/j.susmat.2024.e00953

Arthur J, Bilson Darku F, Owusu AF (2025) Does corporate ESG news impact firm productivity? Financ Res Lett 75:106883. https://doi.org/10.1016/j.frl.2025.106883

Assembly UG (2015) Transforming our world: the 2030 agenda for sustainable development. A/res/70/1. https://www.refworld.org/legal/resolution/unga/2015/en/111816

Baah C, Opoku-Agyeman D, Acquah ISK, Agyabeng-Mensah Y, Afum E, Faibil D, Abdoulaye FAM (2021) Examining the correlations between stakeholder pressures, green production practices, firm reputation, environmental and financial performance: evidence from manufacturing SMES. Sustain Prod Consum 27:100–114. https://doi.org/10.1016/j.spc.2020.10.015

Baldini M, Maso LD, Liberatore G, Mazzi F, Terzani S (2016) Role of country- and firm-level determinants in environmental, social, and governance disclosure. J Bus Ethics 150(1):79–98. https://doi.org/10.1007/s10551-016-3139-1

Barman S, Mahakud J (2025) Energy uncertainty and firm performance: does ESG matter? J Econ Asymmetries 31:00413. https://doi.org/10.1016/j.jeca.2025.e00413

Beckmann J, Rogmann J (2024) Determinants and effects of country ESG controversy. Energy Econ. https://doi.org/10.1016/j.eneco.2024.107326

Beiner S (2025) Sustainable manufacturing measures in practice: insights from leading German manufacturing companies. Proc CIRP 132:203–208. https://doi.org/10.1016/j.procir.2025.01.034

Ben Lahouel B, Bruna M-G, Ben Zaied Y (2020) The curvilinear relationship between environmental performance and financial performance: an investigation of listed French firms using panel smooth transition model. Financ Res Lett 35:101455. https://doi.org/10.1016/j.frl.2020.101455

Ben Lahouel B, Ben Zaied Y, Taleb L, Kočišová K (2022) The assessment of socio-environmental performance change: a benefit of the doubt indicator based on directional distance function and Malmquist productivity index. Financ Res Lett 49:103164. https://doi.org/10.1016/j.frl.2022.103164

Bogetoft P, Otto L (2011) Statistical analysis in DEA. Springer, New York, pp 155–196. https://doi.org/10.1007/978-1-4419-7961-2_6

Brogi M, Lagasio V (2018) Environmental, social, and governance and company profitability: are financial intermediaries different? Corp Soc Responsib Environ Manag 26(3):576–587. https://doi.org/10.1002/csr.1704

Buła R, Foltyn-Zarychta M, Krawczyńska D (2024) Disentangling ESG: environmental, social and governance ratings and financial performance of polish listed companies. Ruch Prawniczy, Ekonomiczny i Socjologiczny 86(1):149–178

Chai S, Cao M, Li Q, Ji Q, Liu Z (2023) Exploring the nexus between ESG disclosure and corporate sustainable growth: moderating role of media attention. Financ Res Lett 58:104519. https://doi.org/10.1016/j.frl.2023.104519

Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444

Chen H-M, Kuo T-C, Chen J-L (2022) Impacts on the ESG and financial performances of companies in the manufacturing industry based on the climate change related risks. J Clean Prod 380:134951. https://doi.org/10.1016/j.jclepro.2022.134951

Chen S, Song Y, Gao P (2023) Environmental, social, and governance (ESG) performance and financial outcomes: analyzing the impact of ESG on financial performance. J Environ Manage 345:118829. https://doi.org/10.1016/j.jenvman.2023.118829

Chen C, Chen S, Wu D (2025a) The impact of ESG performance on r &d investment stability: evidence from china. Int Rev Econ Financ 99:104046. https://doi.org/10.1016/j.iref.2025.104046

Chen M-C, Pang S, Su S-Y (2025b) Sustainable global semiconductor supply chain network design considering ESG. Technol Soc 81:102829. https://doi.org/10.1016/j.techsoc.2025.102829

Cheng LTW, Lee SK, Li SK, Tsang CK (2023) Understanding resource deployment efficiency for ESG and financial performance: a DEA approach. Res Int Bus Financ 65:101941. https://doi.org/10.1016/j.ribaf.2023.101941

Cherchye L, Moesen W, Rogge N, Puyenbroeck TV (2007) An introduction to 'benefit of the doubt' composite indicators. Soc Indic Res 82:111–145. https://doi.org/10.1007/S11205-006-9029-7/TABLES/2

Chowdhury MAF, Abdullah M, Azad MAK, Sulong Z, Islam MN (2023) Environmental, social and governance (ESG) rating prediction using machine learning approaches. Ann Oper Res. https://doi.org/10.1007/s10479-023-05633-7

Cooper WW, Seiford LM, Tone K (2006) Introduction to data envelopment analysis and its uses: with DEA-solver software and references. Springer, Cham, pp 1–354. https://doi.org/10.1007/0-387-29122-9/COVER

Crespi F, Migliavacca M (2020) The determinants of ESG rating in the financial industry: the same old story or a different tale? Sustainability. https://doi.org/10.3390/su12166398

Custódio C, Metzger D (2014) Financial expert CEOS: Ceo's work experience and firm's financial policies. J Financ Econ 114(1):125–154. https://doi.org/10.1016/j.jfineco.2014.06.002

da Silva AV, Costa MA, Lopes ALM, do Carmo GM, (2019) A close look at second stage data envelopment analysis using compound error models and the tobit model. Soc Econ Plan Sci 65:111–126. https://doi.org/10.1016/j.seps.2018.04.001

Duan K, Qin C, Ma S, Lei X, Hu Q, Ying J (2025) Impact of ESG disclosure on corporate sustainability. Financ Res Lett 78:107134. https://doi.org/10.1016/j.frl.2025.107134

Duuren E, Plantinga A, Scholtens B (2016) ESG integration and the investment management process: fundamental investing reinvented. J Bus Ethics 138(3):525–533

Dyson RG, Allen R, Camanho AS, Podinovski VV, Sarrico CS, Shale EA (2001) Pitfalls and protocols in DEA. Eur J Op Res 132(2):245–259. https://doi.org/10.1016/S0377-2217(00)00149-1

Eikon Refinitiv (2023) Business databases & datasets: Thomson. https://eikon.refinitiv.com/. Accessed Jan 2023

Eikon Thomson Reuters (2017) Thomson reuters ESG scores. https://www.esade.edu/itemsweb/biblioteca/bbdd/inbbdd/archivos/Thomson_Reuters_ESG_Scores.pdf. Accessed Dec 2023

European Commission (2023) Corporate sustainability reporting. https://finance.ec.europa.eu/capital-markets-union-and-financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en

Fernández-Sastre J, Montalvo-Quizhpi F (2019) The effect of developing countries' innovation policies on firms' decisions to invest in r &d. Technol Forecast Soc Chang 143:214–223. https://doi.org/10.1016/j.techfore.2019.02.006

Fetting C (2020) The European green deal. ESDN report, ESDN Office, Vienna. https://www.esdn.eu/fileadmin/ESDN_Reports/ESDN_Report_2_2020.pdf

Friede G, Busch T, Bassen A (2015) ESG and financial performance: aggregated evidence from more than 2000 empirical studies. J Sustain Financ Invest 5(4):210–233. https://doi.org/10.1080/20430795.2015.1118917

Giglio S, Maggiori M, Stroebel J, Tan Z, Utkus S, Xu X (2025) Four facts about ESG beliefs and investor portfolios. J Financ Econ 164:103984. https://doi.org/10.1016/j.jfineco.2024.103984

Gospodarowicz M, Korzeb Z, Niedziółka P, Torre A (2024) Financial, spatial and systemic determinants of ESG scoring assigned to commercial banks. Econ Environ 87(4):686. https://doi.org/10.34659/eis.2023.87.4.686

Hoff A (2007) Second stage DEA: comparison of approaches for modelling the DEA score. Eur J Oper Res 181(1):425–435. https://doi.org/10.1016/j.ejor.2006.05.019

Huang X, Liu W, Zhang Z, Zou X, Li P (2023) Quantity or quality: environmental legislation and corporate green innovations. Ecol Econ 204:107684. https://doi.org/10.1016/j.ecolecon.2022.107684

Iazzolino G, Bruni ME, Veltri S, Morea D, Baldissarro G (2023) The impact of ESG factors on financial efficiency: an empirical analysis for the selection of sustainable firm portfolios. Corp Soc Responsib Environ Manag 30(4):1917–1927. https://doi.org/10.1002/csr.2463

Incekara M (2022) Determinants of process reengineering and waste management as resource efficiency practices and their impact on production cost performance of small and medium enterprises in the manufacturing sector. J Clean Prod 356:131712. https://doi.org/10.1016/j.jclepro.2022.131712

International Energy Agency (2024) Energy statistics data. https://www.iea.org/data-and-statistics

Iotti M, Ferri G, Bonazzi F (2024) Financial ratios, credit risk and business strategy: application to the PDO Parma ham sector in single production and non-single production firms. J Agric Food Res 16:101122. https://doi.org/10.1016/j.jafr.2024.101122

Istaiteyeh R, Milhem MM, Elsayed A (2024) Efficiency assessment and determinants of performance: a study of Jordan's banks using DEA and tobit regression. Economies. https://doi.org/10.3390/economies12020037

Iwata H, Okada K (2011) How does environmental performance affect financial performance? evidence from Japanese manufacturing firms. Ecol Econ 70(9):1691–1700. https://doi.org/10.1016/j.ecolecon.2011.05.010

Javeed SA, Latief R, Cai X, San Ong T, Qian S, Haq AU (2022) What is the role of the board sustainable committee for corporate social responsibility? The moderating effect of gender diversity and ownership concentration. J Clean Prod 379:134710. https://doi.org/10.1016/j.jclepro.2022.134710

Kao F-C, Ting IWK, Chou H-C, Liu Y-S (2022) Exploring the influence of corporate social responsibility on efficiency: an extended dynamic data envelopment analysis of the global airline industry. Sustainability. https://doi.org/10.3390/su141912712

Khaw TY, Amran A, Teoh AP (2024) Factors influencing ESG performance: a bibliometric analysis, systematic literature review, and future research directions. J Clean Prod 448:141430. https://doi.org/10.1016/j.jclepro.2024.141430

Kim M, Meivitawanli B (2023) Board characteristics and sustainability ratings of multi-business groups: an evidence from Korean conglomerates (chaebols). E3S Web Conf 426:02017. https://doi.org/10.1051/e3sconf/202342602017

Kim G, Park K, Jeon HW, Okudan Kremer GE (2022) Usage dynamics of environmental sustainability indicators for manufacturing and service systems. J Clean Prod 360:132062. https://doi.org/10.1016/j.jclepro.2022.132062

Knox Lovell CA (1995) Measuring the macroeconomic performance of the Taiwanese economy. Int J Prod Econ 39(1):165–178. https://doi.org/10.1016/0925-5273(94)00067-K

Kunecová J, Bikfalvi A, Marques P (2024) Sustainability orientation, industrial big data and product innovation: evidence from the European manufacturing sector. Comput Ind Eng 191:110163. https://doi.org/10.1016/j.cie.2024.110163

Lei X, Tu Q (2025) ESG performance and innovation in listed manufacturing companies-a prospect theory perspective. Financ Res Lett 72:106603. https://doi.org/10.1016/j.frl.2024.106603

Leung CK, Ko J, Chen X (2025) Economic crises and the erosion of sustainability: a global analysis of ESG performance in 100 countries (1990–2019). Innov Green Dev 4(2):100226. https://doi.org/10.1016/j.igd.2025.100226

Li M, Appiah M, Gyamfi BA, Alola AA (2025) Financialization and environmental policy as drivers of environmental technology in OECD economies. Environ Ecol Stat. https://doi.org/10.1007/s10651-025-00651-z

Liang X, Li J, Guo G, Li S, Gong Q (2021) Evaluation for water resource system efficiency and influencing factors in western china: a two-stage network DEA-tobit model. J Clean Prod 328:129674. https://doi.org/10.1016/j.jclepro.2021.129674

Liao L, Luo L, Tang Q (2015) Gender diversity, board independence, environmental committee and greenhouse gas disclosure. Br Account Rev 47(4):409–424. https://doi.org/10.1016/j.bar.2014.01.002

Lin H, Gu X, Bao X (2025) Corporate ESG performance and bankruptcy risk. Financ Res Lett 76:106987. https://doi.org/10.1016/j.frl.2025.106987

Lins KV, Servaes H, Tamayo A (2017) Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. J Financ 72(4):1785–1824. https://doi.org/10.1111/jofi.12505

Liu X, Zhang C (2017) Corporate governance, social responsibility information disclosure, and enterprise value in china. J Clean Prod 142:1075–1084. https://doi.org/10.1016/j.jclepro.2016.09.102

Liu Y, Zheng L (2025) Impact of pollution control intensity on green innovation of manufacturing enterprises: the role of green finance. Financ Res Lett 76:107027. https://doi.org/10.1016/j.frl.2025.107027

Mahmood Z, Kouser R, Ali W, Ahmad Z, Salman T (2018) Does corporate governance affect sustainability disclosure? A mixed methods study. Sustainability. https://doi.org/10.3390/su10010207

Makri M, Scandura TA (2010) Exploring the effects of creative CEO leadership on innovation in high-technology firms. Leadersh Q 21(1):75–88. https://doi.org/10.1016/j.leaqua.2009.10.006

Martins C, Vaz CB, Alves JMA (2021) Financial performance assessment of branded and non-branded hotel companies. Analysis of the Portuguese case. Int J Contemp Hosp Manag 33(10):3134–3156. https://doi.org/10.1016/j.seps.2018.04.001

Mazzioni S, Soschinski CK, Leite M, Magro CBD, Sanches SLR (2024) ESG performance in emerging economies. Macro Manag Pub Polic 6(1):21–35. https://doi.org/10.30564/mmpp.v6i1.6202

McDonald J (2009) Using least squares and tobit in second stage DEA efficiency analyses. Eur J Oper Res 197(2):792–798. https://doi.org/10.1016/j.ejor.2008.07.039

Melyn W, Moesen W, Economische Studiën KU (1991) Towards a synthetic indicator of macroeconomic performance: unequal weighting when limited information is available. Katholieke Universiteit Leuven, Leuven

Michelon G, Parbonetti A (2012) The effect of corporate governance on sustainability disclosure. J Manag Gov 16:477–509

Mohammadpour S, Javan-Noughabi J, Vafaee Najar A, Zangeneh M, Yousefi S, Nouhi M, Jahangiri R (2020) Factors affecting the technical efficiency of rural primary health care centers in Hamadan, Iran: data envelopment analysis and tobit regression. Cost Eff Resour Alloc. https://doi.org/10.1186/s12962-020-00249-1

Moskovics P, Wanke P, Tan Y, Gerged AM (2024) Market structure, ESG performance, and corporate efficiency: insights from Brazilian publicly traded companies. Bus Strategy Environ 33(2):241–262. https://doi.org/10.1002/bse.3492

Our World in Data (2024) CO emissions by sector. Last accessed 03 March 2025. https://ourworldindata.org/emissions-by-sector

Pedersen LH, Fitzgibbons S, Pomorski L (2021) Responsible investing: The ESG-efficient frontier. J Financ Econ 142(2):572–597. https://doi.org/10.1016/j.jfineco.2020.11.001

Pham TN, Tran PP, Le M-H, Vo HN, Pham CD, Nguyen H-D (2022) The effects of ESG combined score on business performance of enterprises in the transportation industry. Sustainability. https://doi.org/10.3390/su14148354

Phung M-T, Dao V-T, Mai K-T (2024) Dataset for analysing the ESG-oriented technical efficiency of VNSI listed companies. Data Brief 52:109832. https://doi.org/10.1016/j.dib.2023.109832

Qiu Y, Han W, Zeng D (2023a) Impact of biased technological progress on the total factor productivity of China's manufacturing industry: the driver of sustainable economic growth. J Clean Prod 409:137269. https://doi.org/10.1016/j.jclepro.2023.137269

Qiu L, Yu R, Hu F, Zhou H, Hu H (2023b) How can china's medical manufacturing listed firms improve their technological innovation efficiency? An analysis based on a three-stage DEA model and corporate governance configurations. Technol Forecast Soc Chang 194:122684. https://doi.org/10.1016/j.techfore.2023.122684

Rodrigue M, Magnan M, Cho CH (2013) Is environmental governance substantive or symbolic? An empirical investigation. J Bus Ethics 114:107–129

Rupley KH, Brown D, Marshall RS (2012) Governance, media and the quality of environmental disclosure. J Account Public Policy 31(6):610–640

Shewell P, Migiro S (2016) Data envelopment analysis in performance measurement: a critical analysis of the literature. Probl Perspect Manag 14(3):705–713. https://doi.org/10.21511/ppm.14(3-3).2016.14

Simar L, Wilson PW (2007) Estimation and inference in two-stage, semi-parametric models of production processes. J Econom 136(1):31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Spaliara M-E (2011) Financial frictions and the k/l ratio in UK manufacturing. Econ Lett 112(1):23–25. https://doi.org/10.1016/j.econlet.2011.03.015

Sun X, Xiong X (2025) ESG performance and corporate innovation. Res Int Bus Financ. https://doi.org/10.1016/j.ribaf.2025.102817

Teplova T, Sokolova T, Kissa D (2023) Revealing stock liquidity determinants by means of explainable AI: the role of ESG before and during the COVID-19 pandemic. Resour Policy 86:104253. https://doi.org/10.1016/j.resourpol.2023.104253

Tian B, Yu J, Tian Z (2024) The impact of market-based environmental regulation on corporate ESG performance: a quasi-natural experiment based on china's carbon emission trading scheme. Heliyon 10(4):26687. https://doi.org/10.1016/j.heliyon.2024.e26687

Varisco M, Johnsson C, Mejvik J, Schiraldi MM, Zhu L (2018) KPIS for manufacturing operations management: driving the iso22400 standard towards practical applicability. IFAC-PapersOnLine 51(11):7–12. https://doi.org/10.1016/j.ifacol.2018.08.226

Vaz CB, Camanho AS (2012) Performance comparison of retailing stores using a malmquist-type index. J Op Res Soc. https://doi.org/10.1057/jors.2011.63

Wang DD (2019) Assessing road transport sustainability by combining environmental impacts and safety concerns. Transp Res Part D: Transp Environ 77:212–223. https://doi.org/10.1016/j.trd.2019.10.022

Whelan T, Atz U, Holt TV, Clark CC, Salazar P, Liu Z, Bruno C (2021) ESG and financial performance: uncovering the relationship by aggregating evidence from 1000 plus studies published between 2015–2020. https://api.semanticscholar.org/CorpusID:232216565

Wong Y-H, Beasley J (1990) Restricting weight flexibility in data envelopment analysis. J Op Res Soc 41(9):829–835

Xue M, Lu M, Du AM, Zheng B (2025) How do firms respond to climate change? Evidence based on ESG performance. Int Rev Econ Financ 98:103863. https://doi.org/10.1016/j.iref.2025.103863

Zanella A, Camanho AS, Dias TG (2013) Benchmarking countries' environmental performance. J Op Res Soc 64:426–438. https://doi.org/10.1057/jors.2012.62

Zhang C, Zhang S, Zhang Y, Yang Y, Lan K (2024) Does green finance policy contribute to ESG disclosure of listed companies? A quasi-natural experiment from china. SAGE Open. https://doi.org/10.1177/21582440241233376
Zheng Y, Wu Y, Zhang Y, Meng X, Zhang P (2025) Greening the future: how green manufacturing shapes corporate environmental and ESG success. Int Rev Financ Anal 100:103994. https://doi.org/10.1016/j.irfa.2025.103994
Zhu C, Villar AS, Parada Balderrama MJ (2025) Toward sustainability: ESG bridging socioemotional wealth and sustainable financial in family firms. Sustain Futures 9:100470. https://doi.org/10.1016/j.sftr.2025.100470

Authors and Affiliations

Kristina Sutiene[1] · Clara B. Vaz[2,3] · Raminta Vaitiekuniene[1,4]

✉ Kristina Sutiene
kristina.sutiene@ktu.lt

Clara B. Vaz
clvaz@ipb.pt

Raminta Vaitiekuniene
raminta.vaitiekuniene@ktu.lt

1 Department of Mathematical Modeling, Kaunas University of Technology, Studentu 50, Kaunas 15368, Lithuania

2 Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politecnico de Braganca, Campus Santa Apolonia, Braganca 5300-253, Portugal

3 Centre for Management and Industrial Engineering (CEGI), INESC-TEC, Rua Dr. Roberto Frias, Porto 4600-465, Portugal

4 School of Economics and Business, Kaunas University of Technology, Gedimino 50, 44239 Kaunas, Lithuania