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Exploring the Relationship between Financial Performance Indicators, ESG, and Stock Price Returns: A Rough Set-based Bipolar Approach

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ARTICLE INFO	ABSTRACT
Article history: Received 5 October 2023 Received in revised form 17 February 2024 Accepted 4 April 2024 Available online 15 April 2024 ***Keywords:*** Rough Set Theory (RST); DEMATEL; ESG; Multiple Criteria Decision-Making (MCDM).	Using a Rough-Set-based approach, this study investigates the connection between financial performance, Environmental, Social, and Governance (ESG) factors, and stock returns. It analyzes data from various companies and industries to examine how ESG metrics interact with financial indicators to influence stock prices. Those findings underscore the importance of considering financial and ESG factors when evaluating a company's performance and market valuation. The Rough-Set-based bipolar model comprises eight decision rules, and the DEMATEL (Decision-Making Trial and Evaluation Laboratory) analysis reveals the influence relationship among the core attributes. Furthermore, the ranking result, based on the bipolar model, is consistent with the market returns, which suggests the validity of this study.

1. Introduction

In the contemporary landscape of global finance, the intersection of financial performance, Environmental, Social, and Governance (ESG) factors, and stock price returns has become an intricate puzzle that captivates the attention of investors, analysts, and stakeholders alike [1]. The ever-growing emphasis on sustainable and responsible business practices has reshaped the criteria for evaluating a company's success [2]. This study employs Rough Set Theory (RST) [3] as a sophisticated analytical tool to unravel the hidden patterns within the relationship among financial indicators, ESG considerations, and stock price returns.

As markets evolve, investors increasingly acknowledge that financial success is an incomplete metric for evaluating a company's health and long-term viability. Integrating ESG criteria into decision-making reflects a broader societal shift towards sustainable investing. ESG encompasses a wide range of factors, from a company's environmental impact and social responsibility to the effectiveness of its governance structures. The challenge lies in deciphering these diverse variables' interdependencies and structural patterns.

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RST [3], a methodology rooted in mathematics and computer science, has demonstrated its effectiveness in dealing with uncertainty and imprecision in data. Applying RST to this study aims to disentangle the intricate relationships within the financial-ESG-stock price nexus. The theory's capacity to identify essential attributes, dependencies, and decision rules makes it potent for discerning the underlying mechanisms driving market dynamics. Extended from RST, the Dominance-Based Rough Set Approach (DRSA) [4-5] represents a notable extension of the conventional RST, aiming to enhance its utility as a robust decision-support analytical tool. In this study, the DRSA is adopted to conduct rough approximations and induce decision rules, serving as a foundation for forming a bipolar evaluation system.

This research delves beyond traditional analyses, seeking to answer critical questions: To what extent do ESG considerations contribute to a company's financial success? And, perhaps most crucially, how do these elements interact and mutually shape each other?

To address the aforementioned questions, this study employs a rough set-based bipolar model to explore rule relationships among variables, supplemented by Decision-Making Trial and Evaluation Laboratory (DEMATEL) [6] analysis to understand the interactive influence among core attributes. The stocks from TW50 in 2023Q1 and Q2—excluding financial stocks—are used to explore the intricate relationships among financial ratios, ESG indicators, and stock price returns.

Section 2 provides a literature review. Section 3 briefly introduces the methodologies applied in this study. Section 4 adopts a case study from Taiwan to illustrate the proposed approach. Section 5 reveals the result of the case study. Section 6 discusses the result, and Section 7 concludes this research.

2. Literature Review

Exploring the relationship between financial performance indicators, ESG factors, and stock price returns through the lens of RST analysis represents a novel and timely endeavor within financial research. The literature review examines existing studies and highlights key findings that pave the way for the present investigation.

2.1 Financial performance and stock prices

Previous research has extensively explored the link between financial performance and stock prices. Scholars such as Fama and French [7] have demonstrated the significance of financial indicators like profitability, growth, and efficiency in influencing stock returns. The present study mainly follows this direction to select financial indicators. Ligocká and Stavárek [8] examined the relationship between financial performance and stock prices of selected European food companies. Their study shows different indicators reveal diverse outcomes. Likewise, Dzikevičius and Šaranda [9] attempted to answer whether financial ratios help to forecast stock returns; the research suggests that fundamental analysis can be used by modifying specific indicators in the Lithuanian stock market. These studies provide a foundational understanding of the role of financial metrics in shaping market valuations.

2.2 ESG and stock returns

Recent studies have specifically investigated the impact of ESG factors on stock returns. Research by Hong and Kacperczyk [10] found a positive association between corporate social responsibility (CSR) and stock returns. Similarly, studies by Friede *et al.*, [11] and Gompers *et al.*, [12] supported the notion that companies with high ESG scores may exhibit superior stock performance. Thus, the present study aims to incorporate financial indicators and ESG scores to forecast stock returns.

2.3 Rough set theory

The RST introduced by Pawlak, laid the foundations for RST. The theory primarily deals with the approximation of sets through discernibility and indiscernibility relations. Pawlak's mathematical formalism provided a systematic way to represent and analyze uncertainty in data. RST has found extensive applications in decision support systems. Research by Slowinski and Vanderpooten [13] and Greco *et al*., [14] explored rough set-based methodologies for decision rule induction, aiding decision-making in complex and uncertain environments. RST has been applied across diverse disciplines, including finance, medicine, and image processing. Research by Tay and Shen [15] and Slowinski and Zopounidis [16] explored the application of rough set techniques in multiple criteria decision-making (MCDM), demonstrating its utility in extracting meaningful patterns from data.

2.4 RST application in finance

The application of the RST in financial research is a relatively recent development. Research by Pawlak [17] laid the foundation for using RST to handle uncertainty and imprecision in data. Subsequent studies, such as those by Yao and Herbert [18] and Bazan *et al*., [19], have demonstrated the efficacy of RST in financial decision-making, offering a structured approach for uncovering hidden patterns within complex datasets. Shen and Tzeng [20] have provided a series of financial applications using RST, integrated with other soft computing techniques, such as fuzzy inference or fuzzy integral [21].

2.5 DEMATEL analysis

DEMATEL analysis [22] is a systematic and comprehensive approach employed in decision-making processes. This method facilitates the exploration and understanding of complex relationships among various factors by employing a structural modeling technique. DEMATEL enables the identification of causal relationships and interdependencies within a system, helping decision-makers evaluate key elements. By visualizing the cause-and-effect relationships, DEMATEL analysis provides valuable insights into the structure of a problem or decision space, which has gained widespread applications in various fields, including healthcare [23], engineering [24], finance [25-26], and more. This approach is particularly useful in business, management, and policy domains where intricate relationships among variables need to be unraveled for informed decision-making. In this study, DEMATEL is applied to analyze the influential relationships among the core attributes.

2.6 Contemporary perspectives on ESG Integration

Recent literature emphasizes the growing importance of ESG integration in investment strategies. Works by [11] highlight the positive correlation between ESG performance and financial returns, suggesting that companies with strong ESG practices may exhibit superior financial performance and market valuation. This study examines the relationship among financial performance, the ESG indicator, and stock price returns.

In conclusion, the literature on RST reflects its versatility and adaptability in addressing uncertainty and complexity across diverse domains. From foundational principles to practical applications, the evolving landscape of RST continues to inspire researchers and practitioners seeking practical solutions for handling imprecise and uncertain information.

3. Methodology

This research adopts the DRSA approximation to form a rule-based bipolar evaluation model [27-28]. The following introduces the DRSA and the associated rule-based decision model. And the

DEMATEL method is shortly discussed for analyzing cause-effect relationships among crucial attributes.

3.1 DRSA and the bipolar model

The DRSA model initiates by establishing a 4-tuple information system: $IS = \langle U, A, V, f \rangle$, Wherein is a finite set of a universe comprising *n* objects., and A is a finite set of *p* attributes that comprises *p*-1 condition attributes (i.e., *C*) and one decision attribute $D = \{a^D\}$ (i.e., $A = C \bigcup D$ and $C \bigcap D = \varnothing$). V is the value domain of *A*, where *f* is a total function that $f(x, a_k) \in V$ (for each $x \in U$ and $a_k \in A$). An object can be categorized in only one class among a finite set of classes (*Cl*s), such that $Cl = \{Cl_t : Cl_1, Cl_2, ..., Cl_h\}$ for *t* = 1,…,*h*. In this circumstance, an outranking relation $\succeq_{a_k}$ can be defined for any $a_k \in A$ and $o_i, o_j \in U$. If $o_i \succeq_{a_k} o_j$ $(i \le n, j \le n; i \ne j)$, it means "o_i is at least as good as o_j regarding condition attribute a_k". The predefined preference order thus constitutes an upward and a downward union of *Cl*s: (1) $Cl_t^{\succeq} = \bigcup_{s \succeq t} Cl_s$ and (2) $Cl_t^{\preceq} = \bigcup_{s \preceq t} Cl_s$. Thus, if o_i dominates o_j regarding a partial set of C (i.e., $P \subseteq C$), it is a set of objects in U that dominates o_i considering P , which can be denoted as $o_i P o_j$. Thus, if a set of objects is dominating o_i regarding *P*, this set is denoted as $D_P^{\uparrow}(o_i) = \{o_j \in U : o_i P o_j\}$ (i.e., the *P*-dominating set); similarly, if a set of objects is dominated by o_i regarding P , $D_P^{\downarrow}(o_i) = \{o_j \in U : o_j P o_i\}$ (i.e., the P -dominated set). And P -lower and P -upper approximations of an upward union of *Cl*s are defined as Eqs. (1) and (2), and the boundary region of approximation is shown in Eq. (3).

$$\underline{P}(Cl_t^{\succeq}) = \{o \in U : D_P^{\uparrow}(o_i) \subseteq Cl_t^{\succeq}\} \quad (1)$$

$$\overline{P}(Cl_t^{\succeq}) = \{o \in U : D_P^{\downarrow}(o_i) \bigcap Cl_t^{\succeq} \ne \varnothing\} \quad (2)$$

$$Bou_P = \overline{P}(Cl_t^{\succeq}) - \underline{P}(Cl_t^{\succeq}) \quad (3)$$

Therefore, the three categories of rough approximations contribute to the creation of decision rules. The details can be found in [21]. Moreover, the quality of approximation represented by $\varpi_P(Cl)$ is defined in Eq. (4), and the objective of rough approximation is to formulate decision rules with a high level of approximation quality. Additionally, for this study, the DOMLEM algorithm [31] was utilized to generate decision rules, aiming to induce a minimal set of rules that encompass all objects within a decision data table.

$$\varpi_P(Cl) = \left| U - \left(\bigcup_{t \in \{2,...,T\}} Bou_P(Cl_t^{\succeq}) \right) \right| \Big/ |U| \quad (4)$$

The rough approximation thus generates a group of upward union rules that is at least as good as "3," which are deemed positive rules. Similarly, it also generates a group of downward union of rules, the negative rules. In the bipolar model, the supports of each rule need to be normalized so that the total weights are equal to 100% in both positive (i.e., $\sum_{i=1}^{k} w_i^P = 100\%$) and negative groups (i.e., $\sum_{j=1}^{l} w_j^N = 100\%$). The final performance score of each stock is shown in Eq. (5), which implies an object should be more similar to the positive rules and dissimilar to the negative ones.

$$S_g = \sum_{i=1}^{k} w_i^P \times R_{ig}^P - \sum_{j=1}^{l} w_j^N \times R_{jg}^N \tag{5}$$

In Eq. (5), w_i^P and w_j^N denote the normalized supporting weight of the positive and negative rule, respectively. In addition, R_{ig}^P and R_{jg}^N are the scores of the *i*-th positive rule and the *j*-th negative rule. The detailed calculation will be illustrated by a case study in the next section.

3.2 DEMATEL analysis

After rough approximation of the decision table, DRSA can generate a set of the core attributes, which denotes the indispensable attributes. The DEMATEL analysis can unravel the influential relationship among the *n* core attributes.

*Step 1: Construct an initial influence matrix **A***

DEMATEL analysis begins by asking domain experts questions like " What is the influence of criterion *o* on criterion *p* ($1 \le o, p \le n$)?" The DEMATEL questionnaire assigns influence scores ranging from '0 (No Influence)' to '4 (Very High Influence).' The average score of criterion '*o*' on '*p*' will be represented in matrix ***A***, the initial influence matrix, as depicted in Eq. (6).

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1p} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{o1} & \cdots & a_{op} & \cdots & a_{on} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{np} & \cdots & a_{nn} \end{bmatrix}_{n\times n} \tag{6}$$

*Step 2: Transform **A** into a normalized matrix **D***

To compute matrix ***D***, the value of μ calculated using Eq. (7). The resulting normalized matrix, denoted as ***D***, can be obtained by: $\boldsymbol{D} = \mu \times \boldsymbol{A}$.

$$\mu = \max\left\{\max_i \sum_{o=p}^{n} a_{op}, \max_j \sum_{p=1}^{n} a_{op}\right\}, \tag{7}$$

*Step 3: Obtain the total influence matrix **T***

The total influence relation matrix is obtained by summing up the values in the normalized matrix ***D*** to reflect the cumulative influence power *T* ($\boldsymbol{T} = \boldsymbol{D} + \boldsymbol{D}^2 + ... + \boldsymbol{D}^{\infty}$). During the ripple effect, *T* can be indicated as: $\boldsymbol{T}_{n\times n} = \boldsymbol{D}\times(\boldsymbol{I}-\boldsymbol{D})^{-1} = [t_{op}]_{n\times n}$.

Step 4: Calculate the cause-effect coefficients

The total influence matrix, it can sum up each column to have a vector ***R***, where $R = \left[R_1 ... R_p ... R_n\right]$. It may sum up each row to have a vector ***D***, the transpose of vector $R^T = \left[R_1 ... R_o ... R_n\right]$. In here, $R^{\mathrm{T}} + D = \left[R_1 + D_1 ... R_o + D_o ... R_n + D_n\right]$ and $R^{\mathrm{T}} - D = \left[R_1 - D_1 ... R_p - D_p ... R_n - D_n\right]$ can form a cause-effect diagram, where positive $R_p - D_p$ are the cause attributes, negative $R_p - D_p$ the effect ones.

$$T = \begin{array}{c c} & \begin{array}{ccccc} R_1 & & R_p & & R_n \end{array} \\ \begin{array}{c} D_1 \\ \vdots \\ D_o \\ \vdots \\ D_n \end{array} & \begin{bmatrix} t_{11} & \cdots & t_{1p} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{o1} & \cdots & t_{op} & \cdots & t_{on} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{n1} & \cdots & t_{np} & \cdots & t_{nn} \end{bmatrix} \end{array} \tag{8}$$

DEMATEL's cause-effect analysis can help understand the influential relationships between rules, which can identify the influencers.

4. A case study from Taiwan

The research comprises three parts: (1) preprocessing of the data, (2) form a rules-based weighting system and cause-effect analysis, and (3) evaluate sample stocks for ranking.

4.1 Data preprocessing

This research follows the framework proposed by [6], incorporating key financial metrics related to profitability, growth, and debt. The adopted attributes are shown in Table 1. Additionally, it extends the analysis to include an ESG classification index, recognizing the growing importance of ESG factors in investment decision-making. These variables collectively form the basis for forecasting stock price returns, aiming to provide a comprehensive understanding.

Categorizing financial variables using a percentage-based method where the top 1/3 is assigned a value of 3, the middle portion is assigned a value of 2, and the bottom 1/3 is assigned a value of 1. The TESG variable's value ranges from 1 to 4, and all the raw data come from the TEJ (Taiwan Economic Journal) database [29].

. Similarly, the decision attribute, the stock price return in the next period, was divided into 3, 2, and 1, respectively. The data from 2023 Q1 was used as the training set, and the data from 2023 Q2 was used as the testing set. One thing needs attention here: the data from A1 to A12 are at the *t* period, where A13 is the *t*+1.

Table 1
Summary of the condition and decision attributes

Attributes	Symbols	Brief explanation
A1	OPT_Gross	Operational gross profit
A2	OPT_Profit	Operational profit
A3	Taxed_Profit	Taxed profit
A4	R&D_Expense	Research and development expense
A5	Cash_Flow	Cash flow
A6	OPT_Gross_G	Operating gross profit growth rate
A7	OPT_Profit_G	Operating profit growth rate
A8	Taxed_Profit_G	Taxed net profit growth rate
A9	Asset_G	Total asset growth rate
A10	Debt	Debt ratio
A11	TESG	Taiwan ESG score
A12	ROE	Return on Equity
A13	Return	Stock price return

This study adopted the financial data of the TW50 index, excluding financial stocks, to serve as the primary indicators for DRSA approximations. The TESG indicator provided by TEJ was also incorporated. Those data in 2023Q1 (2023Q2) serve as the condition attributes, and the stock price returns in 2023Q2 (2023Q3) as the decision attribute. The attributes used in this study are summarized in Table 1.

4.2 DRSA approximation

By applying DRSA approximation, refer to Eqs. (1)-(3), to the training set by 3-fold cross-validation three times, the average classification accuracy is 60.38%, and the standard deviation is 5.24% while setting monotonic constraints, as shown in Table 2. Monotonic relationships can be viewed as constraints on monotonicity, as they imply that the better the evaluation of an object, the better the decision class should be. In Table 2, the averaged cross-validation and the standard deviation (SD) all reveal superior outcomes while having monotonic constraints. Therefore, in the following approximation, monotonic constraints were applied.

Table 2
3-fold cross-validation of the training set

3-fold cross validation	Standard	Monotonic
1st	66.98%	62.06%
2nd	55.32%	53.30%
3rd	53.22%	65.79%
Average	58.51%	60.38%
Standard deviation (SD)	6.05%	5.24%

Table 3
Bipolar rules and supports

Type	Decision rules	Supports	Support weights
Positive (P1)	(RD_Expense >= 2) & (OPT_Gross_G >= 3) & (ROE >= 3) => (Return >= 3)	4	4/(4+4+3+5+2) =4/18=22.22%
Positive (P2)	(RD_Expense >= 2) & (OPT_Gross_G >= 3) & (TESG >= 4) => (Return >= 3)	4	22.22%
Positive (P3)	(RD_Expense >= 3) & (Taxed_Profit_G >= 3) => (Return >= 3)	3	3/18=16.67%
Positive (P4)	(Asset_G >= 3) & (ROE >= 3) => (Return >= 3)	5	27.78%
Negative (N1)	(TESG <= 1) => (Return <= 1)	2	2/(2+2+4+3)=18.18%
Negative (N2)	(Debt >= 3) & (TESG <= 2) => (Return <= 1)	2	18.18%
Negative (N3)	(RD_Expense <= 1) & (Cash_Flow <= 2) & (TESG <= 2) => (Return <= 1)	4	36.36%
Negative (N4)	(Cash_Flow <= 1) & (OPT_Gross_G <= 1) & (Asset_G <= 1) => (Return <= 1)	3	27.27%

The reclassification accuracy of the training set is 83.33%, and the classification accuracy for the testing set is 72.22%. Due to the adoption of the bipolar model in this study, only rules with D>=3 (i.e., positive) and D<=1 (i.e., negative) are retained. Using DRSA approximation, the obtained rules and the associated supports and support weights are in Table 3. The other rules are listed in Appendix A. An object that satisfies the condition and decision attributes is called a support of the rule. The supports were normalized to obtain support weights for the positive and negative group rules. In the positive rule set, P4 holds the highest weight. N3 holds the highest weight among the negative group of rules.

5. Result

5.1 Bipolar ranking result

Three samples' condition data in 2023Q2 were applied to the bipolar model [28], and the three companies are (1) Lite-On (LO), (2) Quanta (QT), and (3) Chailease Holding (CH). The three companies' condition values in 2023Q2 are summarized in Appendix B (Table B.1). The three companies' scores on those rules and the final scores are shown in Table 4, referring to Eq. (5), which suggests that QT $\succ$ LO $\succ$ CH. In fact, both QT and LO belong to "3," and CH "1". Delving into the exact returns, it indicates the same ranking (i.e., QT $\succ$ LO $\succ$ CH). The bipolar model reveals a consistent result with the market returns, which suggests the validity of this model.

Table 4
Supporting weights and performance scores of the three companies

	Positive rules				Negative rules				
	P1	P2	P3	P4	N1	N2	N3	N4	
weights	0.2222	0.2222	0.1667	0.2778	0.1818	0.1818	0.3636	0.2727	Scores
LO	0.67	1.00	1.00	0.50	0.00	0.00	0.33	0.33	46.67%
QT	1.00	1.00	0.50	0.50	0.00	0.50	0.33	0.33	36.58%
CH	0.33	0.33	0.00	0.50	0.50	0.50	0.67	0.33	-22.99%

Aside from ranking, decision rules obtained by rough approximation also reveal specific patterns. An example is P4, which holds the highest weight. In P4, (Asset_G >= 3) & (ROE >= 3) should be satisfied, leading to superior return in the following period. In the next session, one may decipher what influences those antecedents.

5.2 DEMATEL analysis

In RST, a REDUCT refers to a minimal subset of attributes in a dataset that preserves the ability to distinguish between different classes or categories of data. The intersection of all REDUCTs are the CORE attributes, which refers to the subset of attributes in a dataset that are indispensable for distinguishing between different classes or categories.

The core attributes of the 12 condition variables are (1) R&D_Expense, (2) Cash Flow, (3) OPT_Profit_G, (4) Taxed_Profit_G, (5) Asset_G, (6) ROE, and (7) TESG. This study uses the DEMATEL technique to explore the influential network relationship among those core attributes. Five experts were invited to join this investigation. The experts all have over 15 years of experience in finance, and they answer the question: "To what extent does attribute *i* influence attribute *j*?" The answer ranges from 4 (extremely high) to 0 (no influence). The initial influence matrix ***A*** is shown in Table 5. The total influence matrix ***T*** is in Table 6, and the cause-effect illustration is in Table 7.

Table 5
Initial influence matrix ***A***

	A4	A5	A7	A8	A9	A11	A12
A4	--	2.40	3.20	2.20	1.20	3.00	2.40
A5	1.20	--	1.40	1.20	1.80	1.20	1.20
A7	3.00	2.80	--	3.60	2.80	3.60	1.00
A8	3.60	1.80	1.20	--	3.60	2.80	1.80
A9	0.60	1.20	1.20	1.20	--	1.40	1.40
A11	1.20	0.40	2.80	2.80	3.00	--	1.20
A12	2.80	1.20	3.20	3.20	1.20	3.20	--

Table 6
Total influence matrix ***T***

	A4	A5	A7	A8	A9	A11	A12	R
A4	0.3679	0.4204	0.5435	0.5352	0.4829	0.5960	0.3980	3.3439
A5	0.2683	0.1642	0.2863	0.2966	0.3264	0.3109	0.2197	1.8726
A7	0.5472	0.4643	0.4084	0.6272	0.6007	0.6557	0.3593	3.6628
A8	0.5254	0.3778	0.4360	0.3941	0.5763	0.5643	0.3657	3.2396
A9	0.2193	0.2118	0.2552	0.2747	0.2078	0.2960	0.2129	1.6776
A11	0.3603	0.2630	0.4389	0.4745	0.4904	0.3513	0.2846	2.6630
A12	0.5358	0.3789	0.5642	0.6054	0.5077	0.6325	0.2895	3.5138
D	2.8243	2.2805	2.9324	3.2078	3.1921	3.4066	2.1297	

Table 7
Cause-effect analytics

	Attributes	R	D	R+D	R-D
A4	R&D_Expense	3.34	2.82	6.17	0.52
A5	Cash_Flow	1.87	2.28	4.15	-0.41
A7	OPT_Profit_G	3.66	2.93	6.60	0.73
A8	Taxed_Profit_G	3.24	3.21	6.45	0.03
A9	Asset_G	1.68	3.19	4.87	-1.51
A11	TESG	3.51	2.13	5.64	1.38
A12	ROE	2.66	3.41	6.07	-0.74

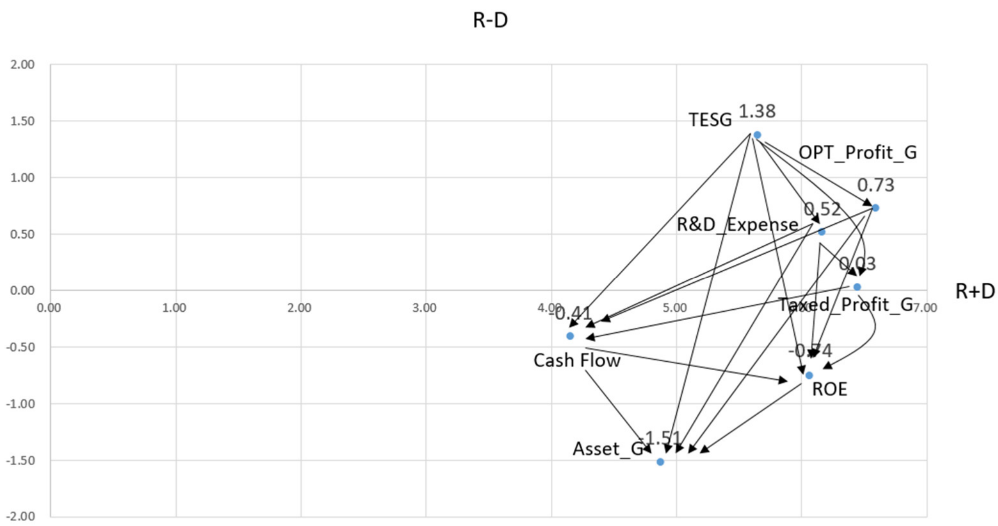

Fig. 1. INRM analysis

Based on Table 7, an influential network relationship map (INRM) can be constructed to depict the influential relationships among the core attributes in Figure 1. This analysis shows that TESG, research and development (R&D) expenditures, and operating profit growth rate serve as sources influencing other indicators. In contrast, asset growth, cash flow, and ROE (Return on Equity) are primarily affected. The influence of TESG is obvious, which echoes previous research [11].

Our findings reveal a nuanced relationship between ESG performance and financial outcomes. While some studies suggest a positive correlation between strong ESG performance and financial success, others propose mixed or inconclusive results. Through the analysis conducted, deeper insights into the mechanisms through which ESG factors impact financial performance are aimed to be provided, along with the identification of potential drivers and barriers to this relationship.

The results of this study have implications for investors, corporate managers, policymakers, and other stakeholders interested in sustainable finance and responsible investment practices. By understanding the link between ESG performance and financial outcomes, stakeholders can make more informed decisions about investment allocation, corporate strategy, and sustainability initiatives.

6. Discussions

Firstly, ESG impacts all financial variables. Using data from FTSE350, Ahmad *et al*., [30] found that ESG exerts a positive and substantial influence on the financial performance of firms. Research suggests that companies with strong ESG practices tend to outperform their peers in terms of financial performance. This is attributed to several factors: (1) Enhanced operational efficiency [31]: ESG initiatives often lead to improvements in resource efficiency, waste reduction, and operational optimization. Companies that adopt sustainable practices can lower their operating costs, increase productivity, and improve overall efficiency, thereby boosting profitability and financial performance. (2) Access to capital [32]: Firms that possess a higher ESG score typically benefit from a lower cost of capital, as investors are placing growing importance on ESG factors when making investment choices. Companies with strong ESG performance are more likely to attract capital from socially responsible investors, leading to lower financing costs and greater access to capital markets. (3) Long-term sustainability [33]: ESG factors are closely linked to long-term business sustainability and resilience. Companies that integrate ESG considerations into their business strategies are better positioned to adapt to evolving market trends, regulatory changes, and stakeholder expectations. By prioritizing sustainability, companies can create long-term value for shareholders and stakeholders while minimizing negative impacts on the environment and society. This study's findings support past research, indicating that ESG positively impacts financial performance and has long-term effects.

Secondly, R&D expenditures affect cash flow, ROE, and asset growth. The relationship between R&D expenditures and cash flow is a crucial topic for discussion. R&D expenditures often represent investments in innovation and future growth opportunities for a company. While R&D investments can lead to the development of new products, technologies, or processes that enhance competitiveness and revenue generation potential, they also require substantial financial resources.

The impact of R&D expenditures on cash flow can be twofold. On one hand, increased R&D spending can result in higher cash outflows in the short term as companies invest in research activities, hiring skilled personnel, acquiring technology, and purchasing equipment or materials. These investments may initially reduce cash flow as expenses outweigh immediate revenue gains.

However, in the long term, successful R&D initiatives can contribute to revenue growth, profitability, and cash flow generation. Moreover, R&D investments can enhance operational efficiency, reduce costs, and increase productivity, ultimately boosting cash flow performance.

Additionally, Tung and Binh [34] discovered that investing in R&D positively influences revenues, profits, and return on equity (ROE), consistent with the findings from the INRM (refer to Figure 1). They also found significant and positive association of R&D expenditure with firm performance, ROA (return on assets) and ROE, in multiple empirical analyses.

In summary, this study primarily finds that ESG affects multiple financial performance indicators, while R&D expenditures also positively influence variables such as ROE and asset growth, supporting previous related research.

7. Conclusions

In conclusion, the application of rough set theory and the DEMATEL technique has provided valuable insights into the relationship between ESG factors, financial performance, and stock price returns. Through the analysis of extensive datasets, a significant impact of ESG considerations on various financial performance indicators, including profitability, operational efficiency, and market valuation, has been identified.

Furthermore, our study has revealed that companies with strong ESG performance tend to exhibit better financial performance metrics and higher stock price returns. This finding underscores the importance of integrating ESG considerations into investment decision-making processes, as it suggests that companies with robust ESG practices may offer greater value and returns for investors.

Moreover, our analysis has demonstrated that R&D expenditures play a crucial role in shaping financial performance, particularly in enhancing variables such as return on equity (ROE) and asset growth. This finding highlights the importance of innovation and investment in research and development for driving sustainable growth and competitiveness in today's dynamic business environment.

Although this study found a positive relationship consistent with past research, it still has several limitations. Firstly, variations in stock market performance across different time periods may influence the study results. Secondly, the DEMATEL analysis relies on the opinions of the five experts, and differences in judgment among experts may exist.

Overall, our study contributes to the growing body of literature on the intersection of ESG, financial performance, and stock price returns by leveraging the analytical power of rough set theory. By providing empirical evidence of the positive relationship between ESG performance and financial outcomes, as well as the significance of R&D investments, our findings offer valuable insights for investors, policymakers, and corporate leaders seeking to navigate the complexities of sustainable finance and responsible investment.

Appendix A

(Taxed_Profit_G >= 3) => (Return >= 2)
(OPT_Profit_G >= 3) & (TESG >= 2) => (Return >= 2)
(Asset_G >= 2) & (ROE >= 3) => (Return >= 2)
(TESG <= 2) => (Return <= 2)
(RD_Expense <= 1) & (Asset_G <= 2) => (Return <= 2)
(Taxed_Profit_G <= 1) & (TESG <= 3) => (Return <= 2)
(TESG <= 3) & (ROE <= 1) => (Return <= 2)
(Asset_G <= 1) & (TESG <= 3) & (ROE <= 2)
(RD_Expense <= 2) & (OPT_Gross_G <= 2) => (Return <= 2)

Appendix B

Table B.1
Three stocks' condition values in 2023Q2

	LO	QT	CH
OPT_Gross	2	1	3
OPT_Profit	2	1	3
Taxed_Profit	2	1	3
R&D_Expense	3	2	1
Cash_Flow	1	2	1
OPT_Gross_G	2	3	3
OPT_Profit_G	2	3	2
Taxed_Profit_G	3	3	2
Asset_G	2	1	3
Debt	2	3	3
TESG	4	4	3
ROE	2	3	2
Return	3	3	1

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Conflicts of Interest
The authors declare no conflicts of interest.

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