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Forecasting the Environmental, Social, and Governance Rating of Firms by Using Corporate Financial Performance Variables: A Rough Set Approach

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Abstract: The environmental, social, and governance (ESG) rating of firms is a useful tool for stakeholders and investment decision-makers. This paper develops a rough set model to relate ESG scores to popular corporate financial performance measures. This methodology permits handling with information in an uncertain, ambiguous, and imperfect context. A large database was gathered, including ESG scores, as well as industry sector and financial variables for publicly traded European companies during the period 2013–2018. We carried out 500 simulations of the rough set model for different values in the discretization parameter and different grouping scenarios of firms regarding ESG scores. The results suggest that the variables considered are useful in the prediction of ESG rank when firms are clustered in three or four equally balanced groups. However, the prediction power vanishes when a larger number of groups is computed. This would suggest that industry sector and financial variables serve to find big differences across firms regarding ESG, but the significance of the model drops when small differences in ESG performance are scrutinized.

Keywords: corporate financial performance; corporate social performance; ESG rating; rough sets

1. Introduction

The practice of corporate social responsibility (CSR) has gained importance over the last few decades [1–3]. This behavior is the result of the globalization of markets and demands for greater transparency and commitment of companies to society. Socially responsible investment dates back to the 19th century, when activism and cooperativism emerged as a means of reconciling business goals with social and ethical ends [4].

Based on Garriga and Melé [5], the main CSR theories are classified as instrumental theories, political theories, integrative theories, and ethical theories. According to instrumental theories, CSR is a strategic tool that allows companies to achieve economic objectives and wealth creation. In this vein, companies bet on ethical and responsible behavior to the extent that this behavior brings competitive advantages to the business. Three groups of instrumental theories can be identified, relying on the economic objective proposed: Maximizing the shareholder value, strategies for achieving competitive advantage, and cause-related marketing. In the first group, the objective is to maximize shareholder value via share price [6–8]. The second group focuses on how to allocate resources to achieve long-term social goals by creating competitive advantages [9–11]. Finally, the third group proposes that the objective of CSR is to broaden the effects of marketing [12–14].

Political theories focus on the effects of excessive corporate power on society and the benefits of responsible corporate power in the political arena. Three approaches of political theories can be distinguished: Corporate constitutionalism, integrative social contract theory, and corporate citizenship. Corporate constitutionalism [15] considers that the company is a social institution, which has social power that must be used responsibly [16]. Integrative social contract theory [17] takes into account the socio-cultural context and normative and empirical aspects of management in a comprehensive manner. This theory argues that social responsibility comes from the consent of society [18]. Lastly, corporate citizenship analyzes the company's activities so that they can be considered as legitimating vis-à-vis society [19,20].

In turn, integrative theories study the identification, channeling, and response of companies to the social demands of stakeholders. Four groups of integrative theories can be identified: Issue management, the principle of public responsibility, stakeholder management, and corporate social performance. The first group deals with the processes by which companies identify, evaluate, and respond to the political and social problems that significantly impact them [21]. The second group was proposed by Preston and Post [22], and focuses on company policies that are not only based on law and regulation, but also on a broad pattern of social direction reflected in public opinion, emerging issues, and implementation practices, amongst others. The third group focuses on the possible effects that business decisions may have on stakeholders [19,23]. The fourth group integrates some of the previous theories and also includes research on social legitimacy [24,25].

Finally, ethical theories study the ethical requirements on which the relationship between business and society is based. As main approaches, it can distinguish the following: Normative stakeholder theory, universal rights, sustainable development, and the common good approach. The first approach was proposed by Freeman [26], and points out that intrinsic value is the common interest of all stakeholders. So, each group of stakeholders should be considered for its own sake and not for its ability to promote the interest of some other group (e.g., shareowners). The second approach considers that human rights is the fundamental basis of CSR [27,28], which led to the emergence of other approaches (e.g., Global Compact). The third approach is aimed at demanding convergence between the three pillars of economic development, social equity, and environmental protection. The fourth approach points out that business, being part of society, must contribute to the common good (e.g., the creation of wealth, the efficient and fair provision of goods and services, and respect for the inalienable and fundamental rights of the individual).

Over the past decades, there has been a growing interest among the scientific community in examining the relationship between corporate social performance (CSP) and corporate financial performance (CFP) [8,29–31]. McWilliams and Siegel [32], for example, point out that there is an ideal level of CSR that can be determined by managers via cost0-benefit analysis, and that there is a neutral relationship between CSP and CFP. Luo and Bhattacharya [33] state that in companies with low innovation capacity, CSR actually reduces the levels of customer satisfaction, which could damage the market value. Charlo et al. [8] argue that responsible firms exhibit a higher systematic risk and have greater size. The authors concluded that being responsible does not translate into lower business results or less stock profitability. Seifert et al. [34] investigated the relationship between corporate philanthropy and the profitability of Fortune 1000 companies, concluding that there is no significant effect on profits from corporate generosity. Finally, Brammer et al. [35] state that firms with higher CSP scores tend to achieve lower returns, while firms with the lowest possible CSP scores outperformed the market.

From an analysis of the above-mentioned works, it is evident that the results obtained are inconclusive and even somewhat in conflict. Some authors argue that the main issue is the correct identification of responsible and irresponsible companies [36–41]. Furthermore, these studies are characterized by being heterogeneous, which hampers comparison [30]. It may therefore be stated that debates regarding the ambiguity of the sign of the relation, the causality of the effect, and moderating and mediating factors are still unresolved. Significantly, the vast majority of studies have focused on the influence of CSP on CFP. In fact, relatively few studies have analyzed the inverse relationship between CFP and CSP, as mentioned by Roberts and Dowling [42] and Julian and Ofori-Dankwa [43]. In these cases, the characteristics of the companies involved in the CSR activities are analyzed. This paper is part of this line of research, which includes the works by McGuire et al. [44], Garcia-Castro et al. [45], Dupire and M'Zali [46], and Lin et al. [47], among others.

It is important to note that CSR is not a variable, and, therefore, it is not measurable [48–50]. Based on the foregoing, the CSR literature has used the term CSP, which is a way of making CSR applicable and putting it into practice [51,52]. However, in agreement with Chen and Delmas [53], CSP measurement addresses a broad spectrum that makes it difficult to generate a proxy that can reflect its full scope. Although CFP measurement addresses performance indicators that are clearly defined and readily available (e.g., return on assets, return on equity, etc.), CSP indicators are not. Due to the qualitative nature of CSP, the assessment of CSP is based mostly on "soft" indicators related to management practices (e.g., philanthropic programs, customer relations, etc.) rather than on "harder" indicators (e.g., toxic releases, tons of CO2 emissions, etc.).

Because of the complexity of CSP measurement, a number of specialized firms, the so-called ESG (environmental, social, and governance) rating agencies, have emerged in the last two decades. These firms provide ESG information and tools for measuring the contribution of companies to sustainable value creation [54]. ESG rating agencies assess and rate the environmental, social, and governance-related business practices of firms throughout the world [2,55,56]. In this vein, these agencies use information collected from each of the companies through questionnaires and analysis of public information (e.g., CSR reports, annual reports, news, etc.), which is examined by interdisciplinary work teams in different geographical areas [57]. Some of the most important ESG rating scores include the Thomson Reuters ESG Score, the Bloomberg ESG Disclosure Score, the Vigeo-Eiris ESG Score, and the MSCI ESG Score. Based on the literature review and to the best of our insight, only a few studies have analyzed the relationship between ESG rating agencies and CFP [58,59]. Nonetheless, the empirical results of these studies are inconclusive. Considering the above introduced consideration, this paper intends to contribute to the extensive literature in this field by employing the Thomson Reuters ESG Score in order to measure the level of CSP. To our knowledge, this approach is one of the first that uses the Thomson Reuters ESG score in academic research about the impact of the ESG rating on CFP.

Regarding the CFP measurement, the academic literature has identified two main options: Accounting-based measures and market-based measures. The first includes ratios such as return on assets (ROA), return on equity (ROE), return on sales (ROS), etc.; the latter includes Tobin's Q, share prices, beta, etc. A comparative analysis of the literature using market measures with those using accounting measures shows that authors, such as Martínez-Ferrero and Frías-Aceituno [60] and Grewatsch and Kleindienst [61], claim that market measures are more adequate for assessment of future and long-term performance. Hillman and Keim [9] point out that market measures capture shareholder value creation without being subject to accounting measure shortfalls. On the other hand, López et al. [62] assert that a firm's behavior can be explained using market indicators, but accounting data are less noisy because they indicates what is actually happening in the company. Moreover, as argued by McGuire et al. [44], accounting measures, especially the return on assets, are better predictors of CSR than market measures, although they also claim that accounting measures are subject to bias from managerial manipulation. Accordingly, since each of the arguments is regarded as adequate as the best way to measure CFP, this study will use both accounting and market variables to gauge financial performance of companies.

The question that arises is whether "doing good by doing well" is possible [63]; in other words, whether or not a committed behavior of companies in CSR terms can lead to good financial results, or, on the contrary, those firms aligned with CSR principles necessarily assume a cost in terms of profitability. Researchers have proposed different mechanisms for analyzing the relationship between CSR and firm performance. The slack resources mechanism proposes that companies engage in CSR because they are doing well financially and have slack resources [47,64–66]. The risk reduction mechanism suggests that CSR may decrease the risk of firms, making it easier and cheaper to obtain financial resources in the markets [67–70]. So, highly leveraged companies have an incentive to engage in CSR activities and improve their CSP. Brammer and Millington [71] argue that a high level of leverage negatively affects the reputation of the company in the financial markets, so they have to perform CSR practices to improve it as a signal of financial strength to market participants. Moreover, high CSP attracts socially responsible investors [72,73], which can have an impact on the cost of capital. Oikonomou et al. [74] find that credit rating agencies take into account the risk-mitigating effects of CSR activities, and award better ratings to firms with better CSR scores. Sahut et al. [75] find that firms' leverage allows them to obtain more financial resources and positively affects their CSR practices. However, this result contrasts the findings of Zwiebel [76], who shows that excessive company debt increases interest expenses, which discourages investment in CSR, as this result is in line with the slack resources hypothesis. The penance mechanism assumes that companies engage in CSR as a form of penance to offset past corporate social irresponsibility and improve the image of the company [77]. Finally, the insurance mechanism states that a good CSR image provides an insurance against future corporate social irresponsibility [78]. Godfrey et al. [79] conclude that CSR activities lead to positive attributions from stakeholders, who then temper their negative judgments and sanctions toward firms because of this goodwill. According to several authors [80,81], companies with high CSP have loyal stakeholders during economic crises. Moreover, Koh et al. [82] expect firms with high CSP to reduce their litigation risk.

Thus, due to their characteristics, some companies can be more likely to engage in CSR activities and have better corporate sustainability performance. According to these theories, companies with slack resources, those that have committed irresponsible actions (penance mechanism), and those that may be involved in socially irresponsible actions in the future (insurance mechanism) have a greater incentive to engage in CSR activities. Consequently, they should have a better score in the ESG evaluations carried out by social rating agencies.

On the other hand, it is important to emphasize that the measurement of socially responsible behavior is carried out by social rating agencies. ESG scores reported by those agencies are supposed to be an accurate proxy for corporate social performance. Social rating agencies collect firms' public information, as well as information directly from the assessed companies, to calculate ESG scores. As proposed by Drempetic et al. [83], it is possible that larger firms often use more resources for providing ESG data for the rating agencies, and may therefore obtain better ESG scores. This would imply the existence of a bias in favor of bigger companies, because ESG scores can be influenced by resources for providing ESG data. In this line, Adams et al. [84], Neu et al. [85], Brammer and Pavelin [86], and Haniffa and Cooke [87] find that the extent of corporate social disclosure is positively related to the size of the company. In addition, Surroca et al. [88] and Lin et al. [47] state that size is one important variable influencing CSP.

Unlike previous works in which the impact of CSR on business performance is analyzed, the aim of this paper is to empirically analyze whether the characteristics of companies have an impact on their ESG rating. In other words, we analyze whether companies' behavior in terms of CSR can be explained by their financial characteristics. Thus, profitability is expected to have a positive impact on the ESG score due to the slack resource mechanism: Those companies with the greatest resources are precisely those who can afford the necessary investments to improve the ESG score. Regarding leverage, the companies that use the financial markets the most are expected to have incentives to improve their ESG score, thus reducing the financing cost. The size of companies can also influence due to a firm size bias. The business sector can cause companies to engage more in CSR activities as a means to improve their image, and avoid fines, penalties, and boycotts by consumers, which would harm future business profits.

In order to deal with a situation where vague and uncertain behavior in data is present, we propose the use of rough sets, a powerful mathematical tool that allows the extraction of information from this context, which is not possible utilizing traditional set theory [89,90].

Our results suggest that ESG scores can be partially predicted by using financial and stock market information, regardless of the discretization parameter used in the rough set model. This gives insights into the relevance of such variables in the environmental, social, and governance performance of firms, which can be used by stakeholders in their investment-decision-making processes.

The paper is structured in the following way. Section 2 introduces the basics of rough set theory and the dataset used in the research. Section 3 discusses the results obtained when applying the methodology to the data from Section 2, and our main conclusions are given in Section 4.

2. Materials and Methods

2.1. Rough Sets

Rough set theory was developed by Pawlak [89]. This methodology is used to define the relation between variables in a context with uncertainty, ambiguity, and imperfect data. Rough sets can be used for pattern recognition and feature selection. They are used in several disciplines, such as finance [90,91], banking [92], engineering [93], medicine [94], etc. The data and their knowledge are associated, but variables with the same information are very indiscernible or similar.

We can define an information system (U, A) by a finite set of objects U and finite set of attributes A. A decision system T is constructed with the information data, and a decision variable based on an attribute not considered in A is added:

$$T = (U, A \cup \{d\}) \text{ where } d \notin A. \tag{1}$$

The elements of A represent conditional attributes that relate any object or variable with one decision attribute. A set of attributes configures a subset B of A ($B \subseteq A$) like a binary relation, called an indiscernibility relation $IND(B)$, on U. This relation is defined when two objects X_i and X_j are equal for every attribute element by the set of attributes of B. In this case, both objects are indiscernible.

$$b\left(X_i\right) = b\left(X_j\right), b \in B \tag{2}$$

An information system $T = (U, A)$ with a set of attributes $B \subseteq A$; given any object $X \subseteq U$, we can use the information inside B to approximate to X. Two operations are defined, the B-lower (B_*) and B-upper (B^*) approximations of X, and they are defined as follows:

$$B_*\left(X\right) = \bigcup_{x \in U} \{B(X) : B(X) \subseteq X\} \tag{3}$$

$$B^*\left(X\right) = \bigcup_{x \in U} \{B(X) : B(X) \cap X \neq 0\}. \tag{4}$$

The B-lower approximation of a set depends on all of the different blocks or partitions of U/B that represent the equivalence classes of indiscernibility relations included in this set of attributes. The B-upper approximation represents the union of all indiscernibility relations that have non-empty intersections with the set of attributes.

Figure 1 represents the upper and lower approximations of X. The area in the black box is the domain U, while the area in the blue curve denotes X, and the orange and green areas denote the B-upper and B-lower approximations of X, respectively.

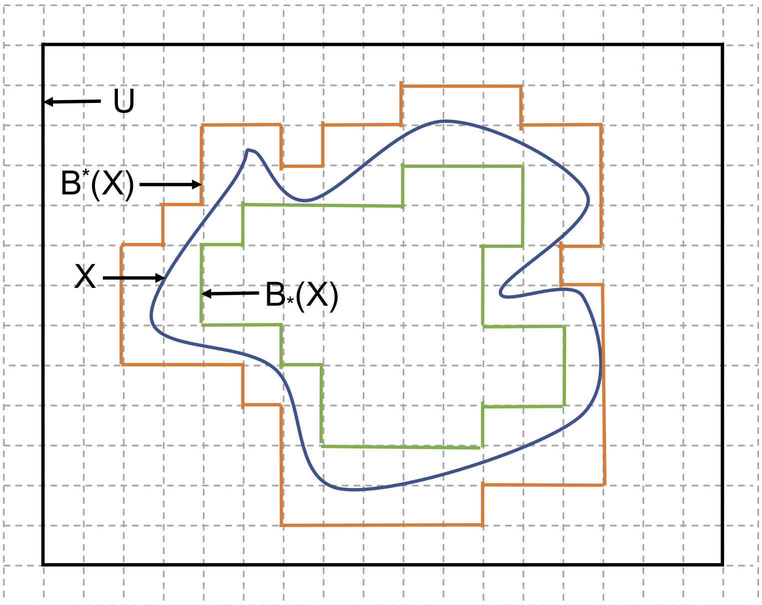

Figure 1. Scheme of the U domain, X set, and B-upper and B-lower approximations of X.

We can define a B-boundary region of X as the difference between the B-upper and B-lower approximations:

$$BN_b(X) = B^*(X) - B_*(X). \quad (5)$$

The B-boundary region represents if the X object is exact or inexact with respect to the set of attributes of B. Then, if the B-boundary region is $BN_b(X) = \emptyset$, the X value is an exact value with respect to a set of B, and when the B-boundary region is $BN_b(X) \neq \emptyset$, X is an inexact or rough object with respect to B.

A B-reduct of X, $RED(B)$, is the minimal subset of attributes that provides the same quality of approximation as the whole set of attributes. This way, attributes not in the reduct can be removed without losing relevant information. The B-core of X, $CORE(B)$, is the intersection of all reducts, i.e., a set with the most significant attributes.

Once reduct computation is performed, the decision rules can eventually be generated by determining the decision attribute value based on the condition attribute values. This process follows the popular IF–THEN form. Each decision is properly assessed based on support, accuracy, and coverage concepts. Accuracy measurement is computed by dividing the support of the decision attribute by the support of the conditional attributes. In order to measure the accuracy of the proposed model in the estimation of the environmental, social, and governance performance, we have divided the number of firms whose ESG group is correctly estimated by the total number of firms. In other words, this accounts for the percentage of firms accurately predicted by the rough set model.

2.2. Data

The data were compiled from Thomson Reuters, which includes information regarding the global environmental, social, and governance (ESG) rating score. ESG ranges from 0 (minimum score) to 100 (maximum score). In addition, stock market and financial information from 2013 to 2018 was also gathered to explain the behavior of ESG scores. According to previous literature, we considered the following independent variables (see Appendix A for a detailed definition of variables):

- ROA: Return on assets
- EPS: Earnings per share
- Size: Market capitalization (in euros)
- D/E: Debt to equity ratio

- Beta: Coefficient Beta, which measures the stock's volatility in relation to the market
- Vol: Trading volume, the amount of securities that were traded during the year
- Sector: Variable that indicates the firm sector

Sector was transformed into binary variables to indicate which sector the firm belongs to (basic materials, consumer, financial, healthcare, industrial, technology, and others).

The sample includes 1688 observations for the covered period. In order to apply the rough set theory on the dataset, we grouped the ESG scores into three balanced groups (each group comprises 1/3 of the total sample size). We can observe significant differences regarding dispersion in all three clusters (Figure 2). The most homogeneous group is the one composed of firms in the central group. The ESG rating for these firms varies between 58.4 and 72.4. The most heterogeneous group is the one related to low-ranked firms. In this case, the ESG scores go from 8.3 to 58.4.

The aim of the rough set model proposed in this paper is to design a rule system capable of predicting the ESG group for each firm, once the values of the independent variables are considered. Although alternative statistical methodologies could be used in this context, the rough set methodology provides some advantages according to the literature: (1) The relative simplicity of interpretation [95], and (2) the use of original variables without requiring any additional requirements or hypotheses, such as probability distributions in statistics [96]. The latter applies to our research in a direct way. Another distinctive property of rough sets is the dimensionality reduction performed through the reduction of the initial table of data. Rough sets eliminate redundant information by means of reducts. A reduct defines the minimum set of variables that conserve the same capacity for classifying the original elements of the original table of observations. This way, the reduct constitutes the most concise way of differentiating among decision classes. Removing redundant information is a powerful alternative to deal with multicollinearity issues observed in some statistical approaches. Notwithstanding this, rough sets have been criticized because of some shortcomings: Unfixed structure and poor universality [97].

If no information was provided to the rough set model, the naive prediction should have a 1/3 chance of guessing the correct ESG group. Hence, a model with a hit ratio of greater than 1/3 is considered a better alternative to the naive model. Such a model would confirm that the variables considered in the research are useful in the explanation of the ESG rating of firms.

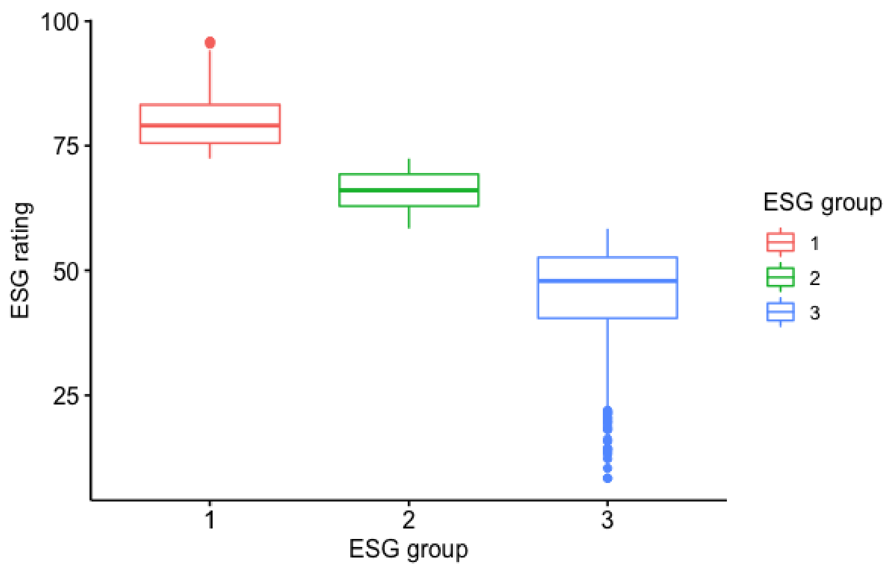

Figure 2. Distribution of environmental, social, and governance (ESG) scores.

Table 1 includes the summary statistics for the independent variables. Profits are measured through ROA and EPS ratios. Negative values represent firms with losses. We can observe a huge variation regarding debt. Some firms have no debt (D/E = 0), while other firms are seriously indebted. The highest value of D/E is 104.875, which translates into a company whose debt is nearly 105 times higher than the book value of the firm. The Beta coefficient also presents a wide range of values, and shows that stock market returns of some companies are uncorrelated with the market (the minimum value is −0.081). We applied the log transformation on the market capitalization in order to manage lower values in Table 1. Regarding the sector, the most frequent one is the Consumer sector, which includes 22.7% of the firms in the dataset.

Table 1. Summary statistics for the variables considered in the research.

Attribute	Mean	St. Deviation	Min	Max
ROA	0.041	0.055	−0.401	0.480
Ln(SIZE)	22.59	1.337	15.79	26.18
EPS	5.325	76.125	−128.543	3121.872
D/E	0.439	2.600	0.000	104.875
Beta	0.883	0.350	−0.081	2.438
Vol	27.10	13.22	8.53	213.50
Materials	0.115	0.319	0	1
Consumer	0.227	0.419	0	1
Financial	0.165	0.371	0	1
Healthcare	0.069	0.254	0	1
Industrial	0.195	0.397	0	1
Technology	0.068	0.252	0	1
Others	0.165	0.367	0	1

3. Results

This section describes the different phases that we followed to apply the rough set methodology to the data introduced in Section 2. The research was carried out by using the software R (version 3.6.2) [98] and the package *RoughSets* (version 1.3.7) [99]. The results are presented in detail and discussed.

The first phase is devoted to generating the input data, i.e., the condition attributes and the decision attribute, along with the decision table for the rough set analysis. The decision table is denoted by $S = (U, A \cup \{d\})$, where $A = \{a_1, a_2, \ldots, a_n\}$ represents the conditional attributes for each company, namely the variables ROA, EPS, Size, D/E, Beta, Volume, and Sector. The decision attribute d is the ESG score given by Thomson Reuters for companies in our dataset.

After performing the generation of the decision table, the second phase consists of discretization (data pre-processing), generation of reducts and rules, and computation of decision rules. The discretization process permits the handling of discrete attributes by partitioning continuous attributes, which is performed through a set of cut points $P_j = \{P_{j1}, P_{j2}, \ldots, P_{jq}\}$. The extreme points P_{j1} and P_{jq} are the minimum and maximum values of attribute a_j, respectively. We used equal-frequency discretization, so each interval contains the same number of objects. In order to perform a sensitivity analysis on the results, we considered different values for parameter q: $q \in \{4, 5, 6, 7\}$. Table 2 shows an example of attribute partitioning where $q = 4$. The values correspond to percentiles 0%, 25%, 50%, and 100%. The discretization process is not applied on binary attributes (sector) because these variables always have the same extreme points: 0 and 1.

Table 2. Discretization through attribute partitioning. Values for the $q = 4$ case.

Attribute	P_{j1}	P_{j2}	P_{j3}	P_{j4}
ROA	−0.401	0.022	0.054	0.480
Ln(SIZE)	15.791	22.046	23.134	26.177
EPS	−14.885	1.420	3.732	3,121.872
D/E	0.000	0.199	0.426	104.875
Beta	−0.081	0.731	0.967	2.438
Vol	8.529	20.866	28.801	213.500

The last phase consists of the computation of all possible reducts. This step is important in rough set analysis "since the reducts can result in obtaining a set of minimal attributes that discern a maximum number of objects through the decision table" [90]. In the first phase, the discretization of data was performed, and this enables the extraction of the core information to generate the reducts. These reducts are necessary for generating the specific rules. Once the reducts are obtained, the decision rules are expressed in the IF–THEN form.

We give some examples of rules in Table 3. For example, rule 1 would translate into the IF–THEN form of Equation (6). This means that the rough set model considers that those firms with attributes ROA, Size, EPS, and D/E in the lower partition, with Beta and Vol in the second partition, and belonging to the healthcare sector are classified in the middle group of the ESG rating (group 2).

$$
\begin{aligned}
&\text{Rule 1}:\\
&\quad IF\\
&\qquad (ROA \in [-0.401, 0.022) \quad \& \quad Ln(SIZE) \in [15.791, 22.046) \quad \& \quad EPS \in [-14.885, 1.420)\\
&\qquad D/E \in [0.000, 0.199) \quad \& \quad Beta \in [0.731, 0.967) \quad \& \quad Vol \in [20.866, 28.801) \quad \&\\
&\qquad Materials = 0 \quad \& \quad Consumer = 0 \quad \& \quad Financial = 0 \quad \& \quad Technology = 0 \quad \&\\
&\qquad Industrial = 0 \quad \& \quad Others = 0)\\
&\quad THEN\\
&\qquad \text{ESG group} = 2
\end{aligned}
\tag{6}
$$

Table 3. A subset of the rules extracted for the $q = 4$ case.

Attribute	Rule 1	Rule 2	Rule 3	Rule 4
ROA	[−0.401, 0.022)	[−0.401, 0.022)	[−0.401, 0.022)	[0.022, 0.054)
Ln(SIZE)	[15.791, 22.046)	[15.791, 22.046)	[15.791, 22.046)	[15.791, 22.046)
EPS	[−14.885, 1.420)	[−14.885, 1.420)	[−14.885, 1.420)	[−14.885, 1.420)
D/E	[0.000, 0.199)	[0.000, 0.199)	[0.000, 0.199)	[0.000, 0.199)
Beta	[0.731, 0.967)	[0.731, 0.967)	[0.967, 2.438]	[0.967, 2.438]
Vol	[20.866, 28.801)	[28.801, 213.500]	[28.801, 213.500]	[28.801, 213.500]
Materials	[0,1)	[0,1)	[0,1)	[1,1]
Consumer	[0,1)	[0,1)	[0,1)	[0,1)
Financials	[0,1)	[0,1)	[0,1)	[0,1)
Industrials	[0,1)	[0,1)	[0,1)	[0,1)
Technology	[0,1)	[0,1)	[0,1)	[0,1)
Others	[0,1)	[0,1)	[0,1)	[0,1)
ESG group	2	2	2	1

The rules given in Table 3 are just a few examples of the rule system extracted by the rough set methodology. Actually, the system reported 762 rules by combining different values in the attributes considered for the estimation of the ESG group. The number of potential rules depends on the reducts extracted during the process, but also depends on the parameter q used in the discretization step.

We carried out four different experiments for $q \in \{4, 5, 6, 7\}$. Doing this, we can analyze how results can change according to the potential number of reducts considered in the process. Eventually, the aim of this procedure was to confirm whether results were robust regardless of the parametrization considered by the decision maker. In order to compare the accuracy of the ESG group prediction, we ran the model 500 times for any value of q. We chose 75% of the sample for training and 25% for testing. Figure 3 represents the distribution of the hit ratio for each experiment conducted. The vertical dotted blue line represents the hit ratio of the naive model. As we have previously mentioned, a naive system would have a probability of 1/3 (33.3%) of guessing the true ESG group correctly. In all four experiments, the mean hit ratio of the rough sets is clearly above the naive hit ratio, thus confirming the suitability of this methodology in the prediction of the ESG rating group regardless of the discretization procedure.

We also analyzed the robustness of the model regarding the number of ESG groups. Figures 4–6 represent the distribution of the hit ratio for four, five, and six equally balanced ESG groups, respectively. The analysis gives insights about the discriminant power of the independent variables when firms are clustered in a larger number of groups. As in the previous experiment, we ran each model 500 times for any value of q ($q \in \{4, 5, 6, 7\}$). Moving from three to four ESG groups reduces the average hit ratio from 51.7% to 42.4%. The threshold that discriminates whether the model performs better than the naive model also drops from 1/3 (33.3%) to 1/4 (25%). As in the case of three ESG groups, none of the 500 runs for each q value performed worse than the naive model. Hence, we can conclude that the independent variables considered in our research have explanatory power on the ESG grouping after splitting the dataset into four equally balanced groups. However, the goodness of the model ceases when firms are clustered in five (Figure 5) or six (Figure 6) groups. There is no improvement in the prediction of the ESG group, and we obtain similar results to those reported by a naive model, where the odds of guessing the correct group by chance are 20% and 16.7%, respectively.

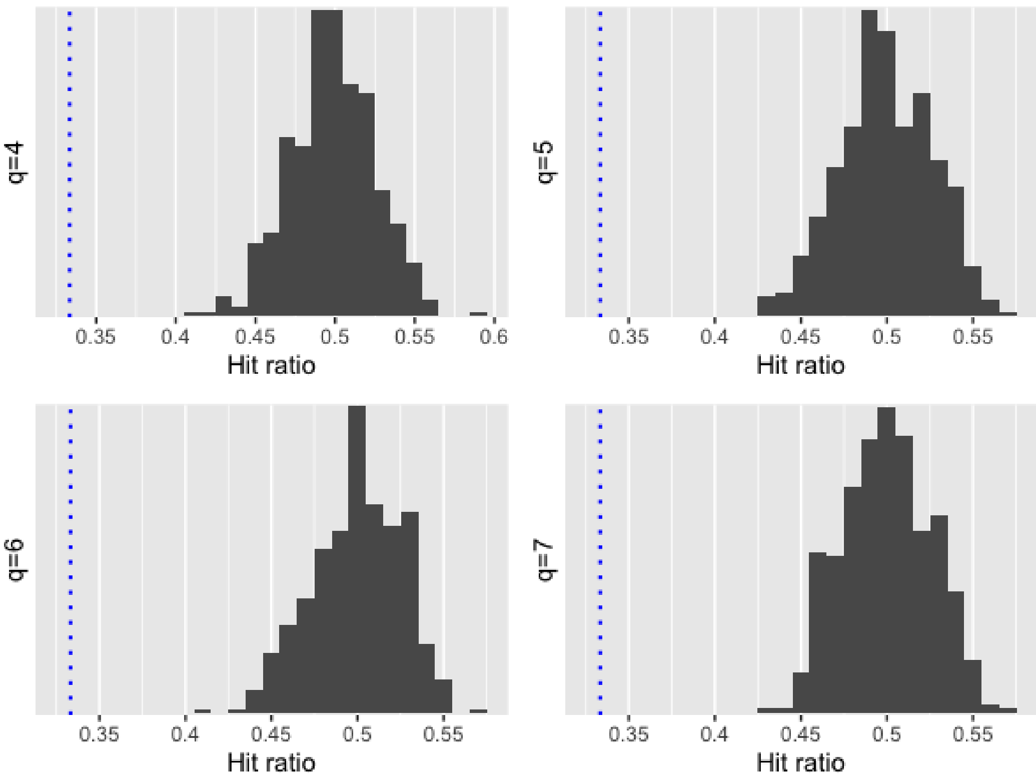

Figure 3. Distribution of the hit ratio; firms are clustered in three ESG groups according to their ESG scores.

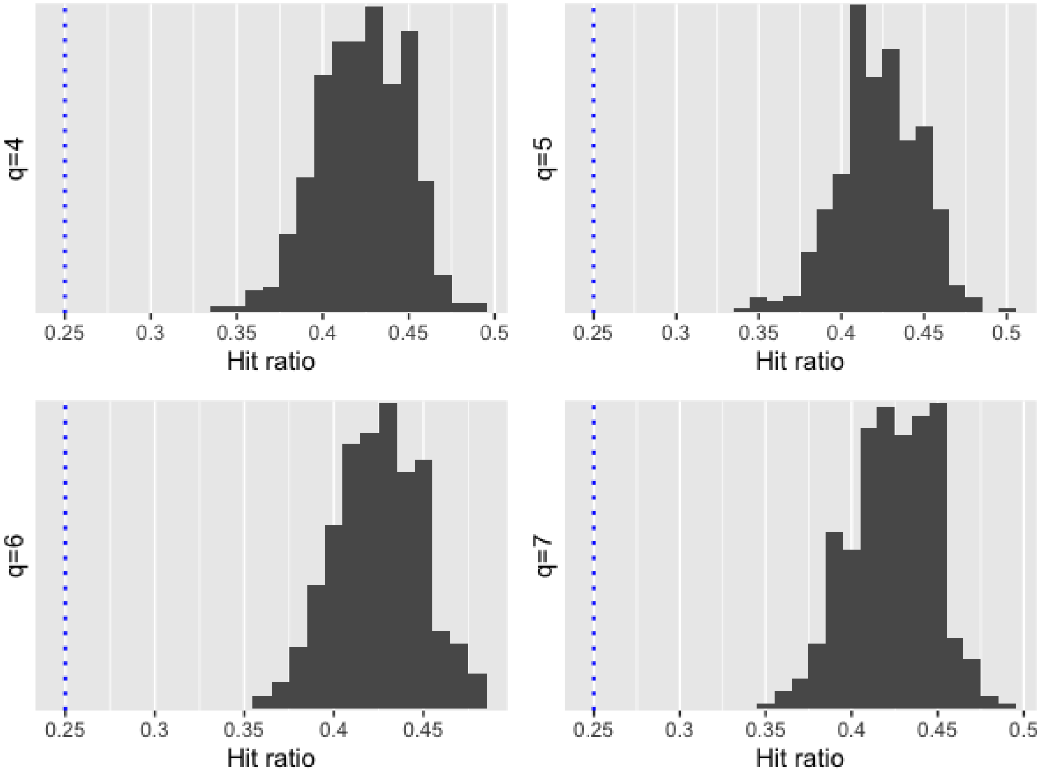

Figure 4. Distribution of the hit ratio; firms are clustered in four ESG groups according to their ESG scores.

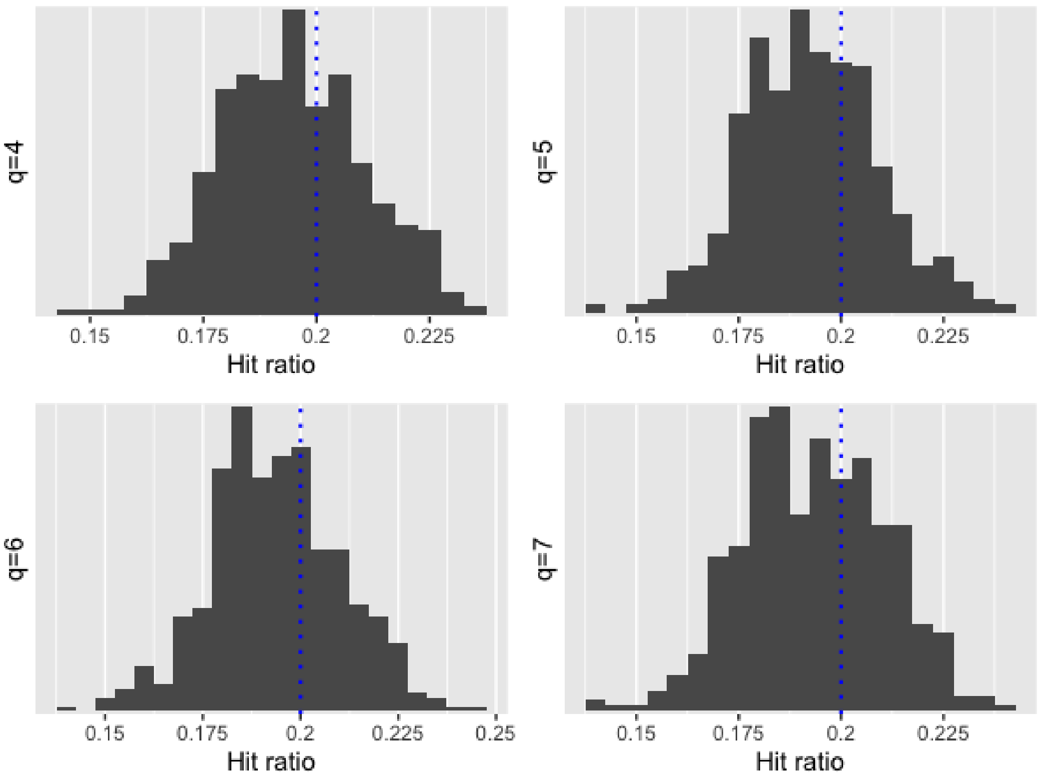

Figure 5. Distribution of the hit ratio; firms are clustered in five ESG groups according to their ESG scores.

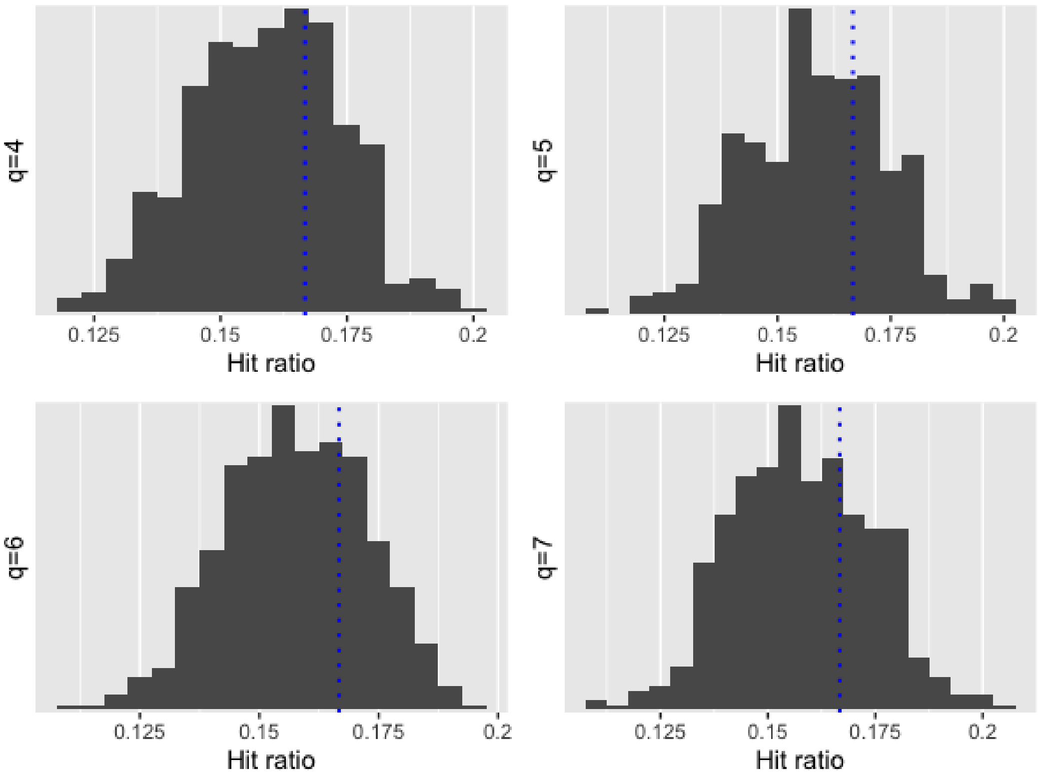

Figure 6. Distribution of the hit ratio; firms are clustered in six ESG groups according to their ESG scores.

The relevance of the explanatory variables was also addressed by performing a regression analysis. The main difference with the rough set approach is that the regression analysis can handle with the original ESG score as the dependent variable, instead of clustering the ESG performance into three, four, five, or six groups. This enables the determination of the statistical significance of each independent variable, along with the statistical significance of the model as a whole. According to the results (Table 4), the regression model explains the 26.9% (adjusted R-squared) of the variability in ESG scores. This value is in line with our previous discussion on how the rough set model tackles the prediction of the ESG group. The higher the number of groups, the lower the discriminant power of the model. The regression model can be viewed as an extreme case of the aforementioned rule, where the maximum number of groups is accomplished: As many groups as observations in the sample. Despite the limited statistical relevance of the model, the p-values confirm the significant relationship between ESG scores and a small group of explanatory variables. The model establishes a positive relationship between the ESG score and the size and beta of the firm. The negative ROA coefficient suggests that firms facing losses are precisely the most engaged in CSR activities, which contradicts the slack resources mechanism. Finally, we can observe that the sector has no significant influence on the ESG score.

Our results show that the economic and financial variables used allow us to correctly predict the relative CSP of companies. The model works best when companies are assigned to three different groups according to their CSP, and loses predictive ability as the number of groups increases. It is interesting to note that the size and ROA variables proved to be significant, as shown in Table 4. The relationship between a company's size and its CSP is one of the hypotheses that appears recurrently in the literature. Thus, larger companies have greater resources to carry out information disclosure of their socially responsible activities and to respond to requests for information from social rating agencies, which could explain their better relative ratings. Therefore, this result is in line with previous research. This is not the case with ROA. In our study, a lower ROA value is related to a better position in the CSR ranking. This is an unexpected result and contrasts with the expectations of the slack resources mechanism and the conclusions of other studies. The difference of the results can be due to the different CSP measures employed. In our study, we use a single score to account for the CSP of the firms. On the contrary, the studies mentioned in the research literature use specific CSP measures regarding different stakeholders and different CSR activities, such as philanthropy.

Table 4. Regression analysis model.

	Estimate	**Std. Error**	**t Value**	***p*-Value**
(Intercept)	−65.649527	6.819537	−9.627	$<2 \times 10^{-16}$ ***
ROA	−46.243597	6.506146	−7.108	1.74×10^{-12} ***
'LN(SIZE)'	5.657986	0.285209	19.838	$<2 \times 10^{-16}$ ***
EPS	0.004602	0.004368	1.054	0.2922
'D/EV'	0.188848	0.128607	1.468	0.1422
BETA	6.346268	1.066307	5.952	3.23×10^{-9} ***
VOL	−0.060161	0.030450	−1.976	0.0483 *
MAT	−0.990511	1.620322	−0.611	0.5411
CONS	0.807097	1.452881	0.556	0.5786
FINANC	−1.325852	1.525423	−0.869	0.3849
INDU	−1.075244	1.475448	−0.729	0.4663
TECH	0.342110	1.815740	0.188	0.8506
OTHERS	−1.845143	1.513648	−1.219	0.2230

Note: Significant codes: '***' 0.001, '*' 0.05; Residual standard error: 13.56 on 1675 degrees of freedom; Multiple R-squared: 0.2739, Adjusted; R-squared: 0.2687; F-statistic: 52.66 on 12 and 1675 degrees of freedom, *p*-value: $<2.2 \times 10^{-16}$.

It is also interesting to note that neither the debt ratio nor the business sector play a decisive role in the classification made by the rough set method. In the case of leverage, this may indicate that the positive effects of debt on the socially responsible behavior of companies (companies with high leverage will engage in socially responsible activities to reduce the cost of capital, improve credit ratings, and attract socially responsible investors, and can have more liquidity to undertake socially responsible actions) are in balance with the negative effects (more debt means higher interest expenses and lower profits, which prevent the implementation of expensive socially responsible actions).

The business sector was included in order to account for the insurance and the penance mechanisms. As the industry sector is often used by investors as a negative screening variable, it is possible that companies in some industries try to compensate this negative image by means of socially responsible activities and obtaining high scores from social rating agencies. It is also possible that companies in sectors that are usually involved in CSR scandals also improve their scores in penance for past activities and to clean their image, or to be prepared for future scandals. As mentioned in the literature research, CSP has been proven to be linked with risk mitigation in the case of negative events and irresponsible activities on an individual basis. In our study, we use a single measure for CSP and do not account for these events specifically. It is probably the case that negative events occur in companies across most or all industry sectors and, as a result, the industry sector is not a useful variable in our methodology.

4. Conclusions

This paper analyzes the relevance of financial information in the prediction of the environmental, social, and governance performance (ESG) of publicly traded European companies. Our results support that financial information has predictive power on ESG. A large dataset composed of European public companies was gathered for the period 2013–2018. Regarding the methodology, we applied the rough set theory, a powerful mathematical tool that allows the extraction of information from an uncertain, ambiguous, and imperfect context.

After performing different experiments by modifying the values of the discretization parameter and the number of ESG groups, the results suggest that the variables considered are useful in the prediction of ESG rank when firms are clustered in three or four equally balanced groups. However, the performance of the model vanishes when a larger number of groups is computed (five and six). This would suggest that the industry sector and financial variables serve to find big differences across firms regarding ESG, but the model becomes non-significant when we search for explanations for small differences in ESG performance scores.

As a future research line, we propose the inclusion of additional financial and non-financial variables and the consideration of a wider dataset of firms. Omitting these variables can bias the estimates and the significance of the proposed framework, which is a limitation in our empirical analysis. Another promising line of research is the consideration of geographical singularities to better understand how the relationship between variables varies depending on the geographical context.

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Abbreviations

The following abbreviations are used in this manuscript:

ESG	Environmental, social, and governance
CFP	Corporate financial performance
CSP	Corporate social performance
CSR	Corporate social responsibility
ROA	Return on assets
ROE	Return on equity
ROS	Return on sales

Appendix A

This section includes the definitions of financial ratios and variables used in the research:
Return on Assets (ROA):

- $ROA = \frac{\text{Net Income}}{\text{Total Assets}}$

Size of the firm (logarithm - $Ln(SIZE)$):

- $Ln(SIZE)$ = logarithm of the market capitalization of the firm (in euros)

Earnings per share (EPS):

- $EPS = \frac{\text{Net Income}}{\text{Outstanding Shares}}$

Debt to equity ratio (D/E):

- $D/E = \frac{\text{Total Liabilities}}{\text{Shareholders Equity}}$.

Beta:

- $Beta = \frac{Cov(r_i,r_m)}{Var(r_m)}$, with r_i = return of the firm i, with r_m = return of the market, $Cov(r_i, r_m$ = covariance between the return of the firm i and the return of the market, and $Var(r_m)$ the variance of the returns of the market.

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