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Does Good ESG Lead to Better Financial Performances by Firms? Machine Learning and Logistic Regression Models of Public Enterprises in Europe

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Abstract: The increasing awareness of climate change and human capital issues is shifting companies towards aspects other than traditional financial earnings. In particular, the changing behaviors towards sustainability issues of the global community and the availability of environmental, social and governance (ESG) indicators are attracting investors to socially responsible investment decisions. Furthermore, whereas the strategic importance of ESG metrics has been particularly studied for private enterprises, little attention have received public companies. To address this gap, the present work has three aims—1. To predict the accuracy of main financial indicators such as the expected Return of Equity (ROE) and Return of Assets (ROA) of public enterprises in Europe based on ESG indicators and other economic metrics; 2. To identify whether ESG initiatives affect the financial performance of public European enterprises; and 3. To discuss how ESG factors, based on the findings of aims #1 and #2, can contribute to the advancements of the current debate on Corporate Social Responsibility (CSR) policies and practices in public enterprises in Europe. To fulfil the above aims, we use a combined approach of machine learning (ML) techniques and inferential (i.e., ordered logistic regression) model. The former predicts the accuracy of ROE and ROA on several ESG and other economic metrics and fulfils aim #1. The latter is used to test whether any causal relationships between ESG investment decisions and ROA and ROE exist and, whether these relationships exist, to assess their magnitude. The inferential analysis fulfils aim #2. Main findings suggest that ML accurately predicts ROA and ROE and indicate, through the ordered logistic regression model, the existence of a positive relationship between ESG practices and the financial indicators. In addition, the existing relationship appears more evident when companies invest in environmental innovation, employment productivity and diversity and equal opportunity policies. As a result, to fulfil aim #3 useful policy insights are advised on these issues to strengthen CSR strategies and sustainable development practices in European public enterprises.

Keywords: ESG; machine learning; logistic regression; return of equity; return of assets; public enterprises

1. Introduction

Nowadays, there is an increasing interest in investment returns, which looks at other aspects other than traditional companies' earnings. This shift actively involves companies which are contributing to the environment, to the society and operate with a transparent governance. This aspect is straightened by the knowledge circulation within the market and the quality of communication between institutions and stakeholders through reports containing detailed, comprehensive and reliable information [1].

According to the 2018 Eurosif European Socially Responsible Investment (SRI) study [2], the ESG integration in investment decisions of 263 asset managers and asset owners in Europe with combined assets under management of 20 trillion Euros in 2017 has grown with a compound annual growth rate (CAGR) of 27% compared to 2015. Among 7 categories of investment decisions considered in the Eurosif study, the ESG investment decision strategy is the fastest growing. Sustainability concerns are seen as a strategic approach to gain market shares, to contribute to the reduction of global emissions and the impacts on the natural environment, while addressing several concerns at societal level [3]. A business sustainability strategy incorporates the essence of the sustainable development concept such as the social vision, economic efficiency and environmental preservation into the daily practices of companies. The social, economic and environmental spheres are thus interconnected such to create a circular supply value chain within the firm. Through this integrated strategy, companies are increasingly achieving a sustainable competitive advantage in the globalized market [4]. Therefore, companies practicing business sustainability may survive longer than traditional businesses and gain market power [5].

The literature agrees that the company's commitment to ESG reduces uncertainty and risk and publicly increases its reputation among investors [6,7]. Therefore, companies that behave irresponsibly with the environment or their employees may generate loss of trust by potential investors. Nonetheless, Garcia et al. [8] argues that this may not be the case for certain industries operating in particular sectors such as '*tobacco, gambling alcohol and adult entertainment*' [8] (p. 136). As a result, these industries are not included in the SRI indicators. Thus, the main difference between SRI and ESG indicators is that the former excludes certain companies, while the latter include all companies that satisfy a comprehensive portfolio concept [9]. The present study focuses on the ESG approach. Furthermore, provided the latest efforts of the European Union to link the capital market with the 2015 Paris agreements in achieving the sustainable development goals, we analyse the case of public companies in Europe.

Furthermore, we consider a combined approach of machine learning and inferential models to investigate ESG metrics. To this end, we contribute to the existing debate [10] with a machine learning approach to predict the accuracy of financial indicators such as the expected Return of Equity (ROE) and Return of Assets (ROA) on several ESG and other economic metrics; and with a logistic regression model to infer on the relationships between ESG factors and ROE and ROA performances of European enterprises.

This paper is structured as follows—Section 2 describes the literature background of ESG practices and financial performance; Section 3 illustrates the machine learning models that are employed in the case study and depicts a description of the sample used; Section 4 provides a description of the obtained results; Section 5 emphasizes a comparative discussion between the obtained results and the international literature and illustrates the main policy implications; and finally, Section 6 concludes the work.

Aims and Contributions

Based on the discussions illustrated above, the present work focuses on the following aims:

- Aim #1. To predict the accuracy of main financial indicators such as the expected Return of Equity (ROE) and Return of Assets (ROA) of public enterprises in Europe based on ESG indicators and other economic metrics. We contribute to Aim #1 with the use of Machine Learning (ML) models on the above mentioned financial indicators.
- Aim #2. To identify whether ESG initiatives affect the financial performance of public European enterprises. We contribute to Aim #2 by empirically testing the existence of any causal relationship between ROE, ROA and the ESG metrics and assessing the magnitude of these relationships. ESG initiatives should positively contribute to the financial performance of European public enterprises in achieving further developments in order to promote social responsibility and sustainable financial solutions.

- Aim #3. To discuss how ESG factors, based on the findings of Aims #1 and #2, can contribute to the advancements of the current debate on Corporate Social Responsibility (CSR) policies and practices in public enterprises in Europe. We contribute to Aim #3 with a comparative discussion between the obtained main results and the international literature and provide useful policy insights on the future developments of such main green practices in European enterprises.

2. ESG Practices and Financial Performances: A Literature Review

Sustainability is changing the way we manage our economies and interact with the ecological systems and the changing environments. The linkage between the society, economy and environment was included in the definition of the sustainable development concept in the Brundtland Report in 1987 and accepted worldwide. In a recent work, Rajesh [11] incorporates this view under a firm's perspective of the supply chain domain and asserts that the sustainability risk is considered an important aspect, as well as that of other risks (i.e., economic, financial) of the firm's business. Thus, the firm should consider the adoption of a business sustainability strategy that meets its present needs, while protecting the ecological system and preserve the natural resources to the future generations [12].

The Global Reporting Initiatives (https://www.globalreporting.org) considers the term economic sustainability of firms as the impacts of an organization on the economic circumstances of its stakeholders and the economic system at all levels of governance. It is generally measured by economic performances, financial indicators, market opportunities and future financial benefits.

The combination of the firm's capabilities to reduce the planet's carbon footprint in the products that it trades, provides an indication of the environmental sustainability [13]. The above capabilities are also emphasized in the firm's contribution, through a lifecycle assessment, to monitoring the changes occurring in the use of natural resources and the compensations that they receive from the human environment (i.e., recycling activities) [14].

The social sustainability considers the relationships between the human resources, which are internal to the firm, with the external (human) relations that it undertakes. Typical issues dealing with the social dimension of sustainability is to ensure employment stability, guarantee health and safety, address human rights and equity of treatment (vertical and horizontal), including gender issues, among all labor force working for the firm [15].

To put into practice the above concepts, the ESG indicators have received international attention since the 2004 Report of the Global Compact [16] and have been widely accepted [17]. The Report stated that 20 of the more influential and largest international financial agencies positively viewed ESG scores as a key factor of a firm's strategy and management. Since then, the relationships between ESG indicators and financial performance attracted the attention of the scientific literature.

Under a supply chain domain, the ESG scores indicate the three dimension of the sustainability above mentioned [18]. When these scores are provided by the various agencies worldwide, they serve as a criterion for investment decisions and collaboration opportunities with the stakeholders [19]. In addition, the ESG scores can perform as guidelines among the firm's competitors and be reviewed cyclically to provide the market with further indications of the sustainability improvements of the firm [20].

In a recent study by Niesten et al. [21], the role of collaboration and networking between the firm's and its stakeholders is emphasized. The creation of interpersonal trusts plays an important role for the implementation of innovative technologies reducing waste and improving the environmental and social performance of the firm.

Lokuwaduge and Heenetigala [22] argue that the stakeholder engagement is vital to boost the firm's environmental policy, sustainability attitudes and investment decisions. The study also discusses the lack of harmonization in reporting the ESG scores and proposes the development of an ESG index which is reliable and can be used by the stakeholders as a benchmark to compare sustainability initiatives of the firms. Husted and de Sousa−Filho [23] highlight the role of collaboration as a key element to improve sustainability performance of the firm. In particular the authors suggest that collaborative projects, compared to in−house and out−sourcing governance, achieve the greatest score of ESG performance.

In terms of gender issues, the work by Arayssi et al. [24] investigates the role of women directors on corporate boards in sustainability reporting and shareholders' performance. The study is based on a panel of firms included in the Financial Times Stock Exchange 350 index between 2007 and 2012. The work considers the Bloomberg social disclosure score on the firms' risk and performance. The main findings reveal that the presence of women directors on corporate boards in sustainability reporting positively affects the firm's risk and performance and is seen as an opportunity to invest in social engagement.

Garcia et al. [8] address the gap of ESG performance in sensitive industries (i.e., those industries which are more likely to damage the environment and rise social concerns than others) of the BRICS countries (Brazil, Russia, India, China and South Africa). The study uses the Thomson Reuters Eikon database to investigate a sample of 365 companies between the time period 2010–2012. The major result is that, surprisingly, sensitive industries, when controlling for the size and country, presents high ESG performance which, in turn, positively affects financial indicators.

More recently, the work by Escrig−Olmedo et al. [25] investigates how the criteria to set the ESG score evolved over a 10 year time period across various international rating agencies. Main results suggest the rating agencies have refined their ESG parameters to address the sustainability changes occurred at global level. Nonetheless, the authors argue that there is still space for rating agencies to accurately select and compute their ESG scores in the near future and fully capture a sustainability assessment process at firm level.

3. Materials and Methods

The first part of the present section deals with a theoretical description of the ML models used in our work. The last part of the section provides an overview of the database and the selected variables.

3.1. Machine Learning Models

ML is a method for analyzing data with which an artificial intelligent agent learns, identifies patterns, makes decisions and improves its learning over time like humans do [26]. From this perspective, ML extracts knowledge from structured and unstructured data which are used for predictions and generates new information and knowledge. Thus, ML reduces the bias due to uncertainty and provides indications on problem solving issues. ML has been widely used in financial and economic analysis particularly in the energy market [27] and has recently gained attention in the field of financial economics [28] and sustainability [29].

In supervised machine learning [30], the learner is first presented with a training dataset in which each data item includes values for a number of attributes or features including one marked attribute which we wish to be able to predict. From these datapoints, a model is constructed which is a function mapping the input features of a datapoint onto a predicted output value. In essence, the role of the learner is to notice the relationships between the feature of interest and the other features and create a rule that abstracts this knowledge from the data [31]. The way in which the model is created depends on the learning algorithm used. Indeed the representation of the model varies depending on the algorithm used. The model can then be used to predict the value of additional previously unseen instances by supplying the input attributes to the model and recording the output. By making predictions for a test dataset (which is not used during learning but which has known output attributes), the correctness of the model can be assessed. The following subsections outline the models used in this study.

3.1.1. Random Forest

Decision trees [32] are a well−known machine learning technique. All data points are initially associated with the root node of the tree and some decision test of these points is used to partition the data, with a distinct child node being created for each block of the partition. There are very many decision tests that could be used with the method for choosing the test varying between algorithms. Typically, one seeks to partition the data in such a way as to have the dependent feature as homogeneous within each partition as possible, with measures such as Kullback−Leibler divergence being used to assess this [33]. Splitting of the nodes in this way continues recursively until the algorithms halting conditions are met, typically when the dependent variable has the same value for every datapoint associated with the node. When used for regression, the previously unseen datapoint moves from the root of the tree through the path defined by the given tests. When it reaches a leave node, a prediction based on the values of the datapoints at that node is made. ID3 [34] and C4.5 [35] were the most widely used decision tree building algorithms for many years, though CART [36] is now extensively used as well.

Random forests are an extension of decision trees, in which a large number of decision trees are learned and the overall output of the forest is based on the outputs of the individual trees [37]. This avoids the overfitting sometimes encountered when using a single decision tree [38]. It is essential to the algorithm that there is diversity amongst the structure of different trees [39]. This can be achieved by limiting each tree to be learned from only a random subset of the available features [40]. Having obtained regression values from each tree, these need to be combined into an overall prediction. For regression, a simple arithmetic mean of the values from each tree can be used [M 38].

3.1.2. Support Vector Regression

Support vector regression aims to create a linear regression in a similar way to ordinary least squares regression. However, rather than find the line which exactly minimizes the error term, a line is found in which all actual values fall within a small distance of their predicted value [41]. In practice, such a line may not exist and therefore the formulation is usually extended to allow points to fall outside the boundary with a penalty for doing so. The result is a that a line is found which maximizes number of points within a set distance of the line minus the absolute error to the points beyond this distance.

In order to allow non−linear relationships to be modelled, the well−known 'kernel trick' is used [42]. Each point in the dataset can be implicitly mapped to a higher dimensional space without explicitly calculating this space. The linear regression outlined above can then take place within this space, leading to regressions which are highly non−linear in the original data space.

3.1.3. K−nearest Neighbor

In its basic form, K−nearest neighbour is one of the simplest machine learning algorithms available. During training, data points are simply stored. No explicit predictive model is created at all. As such, it can be seen as a form of case−based learning or lazy learning [43]. When a prediction must be made for a new point, the k points in the training data which have the lowest metric distance to this new point are retrieved and utilised. The metric used to determine the nearest neighbour may vary depending on the application, but typically used measures for numeric data include Euclidian or Manhattan distances.

k is a fixed quantity and can either be specified by the user or a good value be found automatically through techniques such as cross validation [44]. Smaller k means that the predictions are influenced by a smaller part of the solution space, allowing much more complex functions to be represented. However, the reliance on fewer examples means that such predictions are far more prone to overfit and vulnerable to noisy data. In the case of regression, the predicted value is the value associated with each of the k nearest neighbours weighted by their relative closeness to the point.

3.1.4. Artificial Neural Network

Artificial neural networks are inspired by the neurons found in animal brains [45]. A number of these neurons can be connected together in layers, with the outputs from one layer forming the inputs to the neurons in the next layer [46]. Each artificial neuron performs a simple calculation (such as a weighted sum) to set its output to be a function at its inputs. Typically, a neuron conducts a weighted sum of its inputs then passes this value through some activation function to introduce non−linearity into the system. The form of the activation function can vary considerably, but commonly used examples include many sigmoid functions [47] and rectified linear units [48].

Learning with an artificial neural network consists of setting the weights in each of the neurons such that each input data item in the training set produces the expected output as closely as possible. The backpropagation algorithm [49] allows the weights to be appropriately set, by effectively dividing any discrepancy between the actual and predicted output value amongst the nodes of the network. The weights can then be tuned appropriately using some form of stochastic gradient descent [50].

3.1.5. Ridge Regression

In datasets with multicollinearity, standard linear regression can develop large variances [51]. This leads to overfitting of the data. The bias−variance trade−off [52] suggests that a slight and acceptable increase in bias may massively reduce the variance and lead to a model with much lower error overall. Ridge regression adds this bias but slightly increasing the value of the leading diagonal in the correlation matrix (the 'ridge').

3.2. Inferential Model

To try to capture any causal relationship between the ROA and ROE and the ESG variables we consider two logistic regression models, one for each outcome variable. In particular, we consider the normalized and discretized data obtained from the ML analysis and use it for the inferential model. After normalization and discretization, the ROA and ROE appear as categorical variables. We are aware that the discretization removes information. Nonetheless, it was a necessary step to obtain accurate predictions of the ML study. The ROA and ROE values are each grouped into 10 decile classes.

As a result, for the purpose of our inferential investigation, we employ an ordered logistic regression model. Similar to logistic regression models, ordered logistic models are generally used to test the relationship between a categorical variable and one or more categorical or continuous predictors. An ordered logistic regression assumes an S−shaped curve. A linear transformation is applied to the dependent variable because of non−linear extreme values and an error term which is not normally distributed and not constant across data [53]. Ordered logistic regression models are based on the assumption of the independence of irrelevant alternatives (IIA) condition. This assumption states that the choice in one category is exclusive. The parameters of the ordered logit model are generally estimated through Maximum Likelihood estimator (MLE), where the likelihood function for discrete values is defined in terms of the probability that that particular value is realized [54].

3.3. Data, Sample and Descriptive Statistics

Hill [9] recognizes several rating agencies that provide data and information on ESG scores. In the present work, we use the trial version of the Thomson Reuters ASSET4/EIKON database. The trial version allows to download a maximum of 5000 observations. This database has been already used by several scholars [55–57]. The ESG scores are available since 2002 [58] for more than 7000 firms and the metric contains more than 450 data points which constitute the aggregate variables for the categories 'Environmental,' 'Social' and 'Governance.' The aggregate variables are classified as follows—Resource use, Emissions and Innovation for the category Environmental; Workforce, Human Rights, Community and Product Responsibility for the category 'Social'; and Management, Shareholders, CSR strategy for the category 'Governance.'

Our final sample contains 1038 public companies that have their business in Europe. Data considers the fiscal year 2018–2019. Table A1 (in the Appendix A) illustrates the number of firms per Global Industry Classification Standard (GCSI) and country. All countries are well represented with five major economies such as the UK, Germany, France, Sweden and Switzerland comprising 60% of the total sample. Similarly, all sectors are well represented in the sample. The top three industries refers to the industrial (20%), financial (16%) and consumer discretionary (12%) sectors.

Table A2 (in the Appendix A) shows the description of the variables considered in our database and Tables 1 and 2 illustrate a descriptive statistics of the sample. In Table 1, the environmental domain appears with mean values ranging from 61% (s.d. 26%) of the environmental innovation score to 69% (s.d. 23%) of the resource use score. The mean value of CO_2 equivalent emissions is in the figure of 2,6 millions (s.d. 24 mln). In terms of the social domain, the average number of employees in the CSR reporting and the number of women employees present low mean percentage values with 33% and 38%, respectively; while the average employment productivity is in the figure of 31 thousand Euros per year (s.d. 66 thousand Euros per year). The remaining mean values of the social domain range from 56% (s.d. 152.5%) of the hourly pay gaCSRp between male and female employees, the product responsibility score (62% with s.d. 28%), the workforce score (70% with s.d. 22%) and the human rights score (74% with s.d. 23%). The mean values of the governance domain refer to the average board tenure of about 6 years (s.d. 2.59), the management score (55% with s.d. 29%), the CSR strategy score (56% with s.d. 27.08%) and the board meeting attendance of 95 days per year (s.d. 6 days per year). Finally, we report the mean values of our financial variables of interest such as the ROE and ROA. These are about 14% (s.d. 90%) for the former and 6% (s.d. 10%) for the latter.

Table 1. Descriptive statistics of continuous variables in the original dataset.

Variable	Obs	Mean	Std.Dev.	Min	Max
Emission score	1038	67.92	23.96	0.08	99.81
CO_2 equivalent emissions	1038	2.54	12.18	0	188
Resource use score	1038	69.29	23.16	0.08	99.92
ESG score	1038	62.02	15.61	8.25	95.94
Environmental innovation score	1038	61	25.82	0.28	99.92
Salary gap	1038	56.41	152.5	0.63	3877.27
Number of employees in the CSR reporting	1038	32.32	68.48	0.02	664.50
Number of women employees	1038	37.36	15.34	1.6	88.13
Workforce score	1038	68.70	22.11	1.18	99.88
Human rights score	1038	73.87	23.21	11.64	99.78
Product responsibility score	1038	62.08	27.62	0.08	99.85
Average employment productivity	1038	30.70	66.36	0.004	634.50
Average board meeting attendance	1038	95.01	6.09	14	100
Average board tenure	1038	5.95	2.59	0.25	18.96
Management score	1038	54.82	28.78	0.42	99.64
CSR strategy score	1038	56.28	27.08	0.37	99.78
Change in company market cap	1038	−13.12	44.39	−91.3	875.8
Operating income	1038	935.57	2083.65	0.685	33281.1
Net income	1038	842.01	1697.62	1.15	14718.29
Change in total equity	1038	13	78.53	−199.4	1445.6
ROE	1038	13.83	90.54	−2083.3	1190.6
ROA	1038	5.98	9.68	−38	227.1

CSR: Corporate Social Responsibility, ROE: Return of Equity, ROA: Return of Assets.

Table 2. Descriptive statistics of categorical variables in the original dataset.

Variable Name	Frequency	Percent
Water efficiency policy		
0	448	43.16
1	590	56.84
Energy efficiency policy		
0	142	13.68
1	896	86.32
Sustainable development policy		
0	846	81.50
1	192	18.50
Environmental management team		
0	489	47.11
1	549	52.89
Environmental management training		
0	429	41.33
1	609	58.67
Diversity & opportunity policy		
0	57	5.49
1	981	94.51
Health & safety policy		
0	85	8.19
1	953	91.81
Training and development policy		
0	69	6.65
1	969	93.35
CSR sustainable development committee		
0	340	32.76
1	698	67.24
CSR corporate governance board committee		
0	808	77.84
1	230	22.16
Career development policy		
0	106	10.21
1	932	89.79
Esg score grade		
1	1	0.10
2	1	0.10
3	15	1.45
4	31	2.99
5	57	5.49
6	138	13.29
7	152	14.64
8	206	19.85
9	205	19.75
10	158	15.22
11	66	6.36
12	8	0.77
Environmental innovation score grade		
1	12	1.18
2	17	1.67
3	41	4.04
4	104	10.24
5	172	16.93

Table 2. *Cont.*

Variable Name	Frequency	Percent
6	49	4.82
7	69	6.79
8	56	5.51
9	106	10.43
10	142	13.98
11	94	9.25
12	154	15.16
CSR strategy score grade		
1	41	4.02
2	64	6.27
3	73	7.16
4	47	4.61
5	111	10.88
6	101	9.90
7	82	8.04
8	55	5.39
9	158	15.49
10	67	6.57
11	107	10.49
12	114	11.18

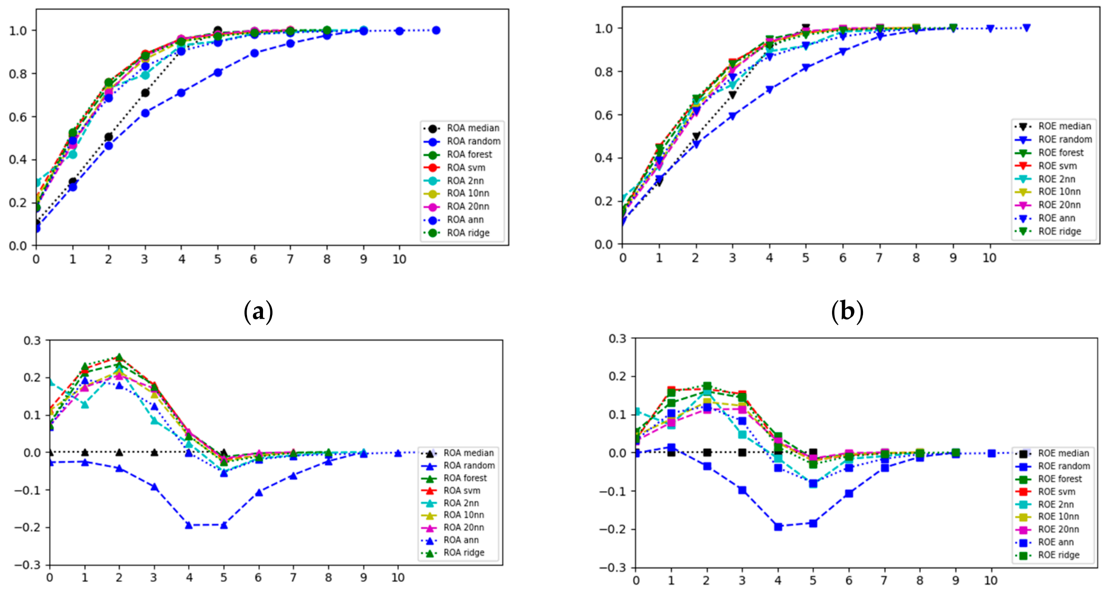
In Table 2, energy efficiency policies have the highest priority in the investment agendas of about 86% of public companies in Europe. These are followed by environmental management training (59%) investments, water efficiency policies (57%) and the presence of environmental management teams (53%). Similarly, the social dimension shows how career development policy as well as diversity and opportunity, health & safety and training and development policies are almost present in the majority of the sample (90–94%). These values are followed by the presence of a CSR sustainable development committee (67%) and a CSR corporate governance board committee (23%). In terms of ESG score grades, 20% of companies present a good performance between 8/12 and 9/12 points. As for the environmental innovation score grade and the CSR strategy score grade, we can observe the presence of a binomial distribution among firms. This means that there are two groups of companies which show either high performances (12/12 points representing 15% of the sample; and 10/12 points, representing 14% of the sample) or low performances of environmental innovation (4–5/12 points representing 10–16% of the sample, respectively). Similarly, as for the CSR strategy score grade there exists a group of companies (11%) which shows low performances (5/12 points) and another one which shows high performances such as 11/12 and 12/12 points representing 10 and 11% of the sample, respectively.

4. Results

This section describes, in the first part, the main findings of the ML study and in the second part the main results of the logistic regression model.

4.1. ML Results

Figure 1 illustrates the predictions of the ROA and ROE with the ML models considered in Section 3. Predictions have been performed in Python (https://www.python.org/) using a 10−fold cross validation with algorithms from the sklearn library with default parameters, except varying k as k = 2, k = 10 and k = 20 in the k nearest neighbors model.



(**a**) (**b**)

(**c**) (**d**)

Figure 1. (**a**) Cumulative distribution of distance between predicted Return of Assets (ROA) and actual ROA; (**b**) Cumulative distribution of distance between predicted Return of Equity (ROE) and actual ROE. (**c**) Comparison of ROA distributions in panel (**a**) minus the baseline prediction (ROA median); (**d**) Comparison of ROE distributions in panel (**b**) minus the baseline prediction (ROE median). Table A3 shows the legend of the models used to train ROA and ROE.

As it can be noted in panels (a) and (b) most of 20% of instances are perfectly predicted by most algorithms, 30%–50% are predicted to within one decile and 40–70% are predicted to within the second decile of the true value. Panels (c) and (d) show the values from the top panels minus the performance of a baseline prediction (which is the median value). If a line is above zero in these panels, it means the methods perform better than the baseline. In this case, all models perform well, but the ROA and ROE Random. Intuitively, this seems a second baseline which makes an entirely random prediction for each instance for both ROA and ROE. As predictions perform better than the baselines, we can argue that there is information in the environmental, social and governance variables (i.e., the inputs) that allows the ROA and ROE to be predicted. In other words, there exists a relationship between the input variables and the returns. Can this relationship be tested? Section 4.2 responds to this question.

4.2. Logistic Regression Results

Tables A4 and A5 (in the Appendix A) illustrate the estimates of the inferential analysis. The diagnostic test at the bottom of the table suggests that the model satisfies the proportional odds assumption. As for the ROE model, results suggest that the determinants of the probability affecting the ROE and which are statistically significant are the following:

- Sustainable development policy(+), Diversity & opportunity policy(+), Salary gap(+), Average employment productivity (+);
- Environmental management team (−), Environmental management training(−), Number of women employees (−), CSR corporate governance board committee (−).

Generally, we can interpret the signs of the ordered logistic regression output but not the magnitude of the estimated coefficients. In the case of categorical predicted variables, negative signs would indicate that a higher scale of the predictive variable is more likely to affect lower categories of the dependent variable. This means that the magnitude can be higher, for example, in the first, second or third deciles of the dependent variable and vice−versa.

To interpret the results of the magnitudes, we refer to the estimated predicted probabilities in Tables 3 and 4. In Table 3, the Sustainable development policy positively affects the fifth−tenth ROE deciles in the range of +10–12%. A similar finding can be reported for the Diversity & opportunity policy (+11%). CSR corporate governance board committee increases by +12% the second and third ROE deciles. For both the Environmental management team and Environmental management training an increase by +11% is found in the third and fourth deciles.

Table 3. Predicted probabilities ROE model (Delta−method).

	Margin	**P > z**	**Margin**	**P > z**	**Margin**	**P > z**
Sustainable development policy			Diversity & opportunity policy		CSR corporate governance board committee	
1	0.07	0.00	0.09	0.00	0.12	0.00
2	0.08	0.00	0.09	0.00	0.12	0.00
3	0.09	0.00	0.10	0.00	0.12	0.00
4	0.10	0.00	0.11	0.00	0.17	0.00
5	0.10	0.00	0.11	0.00	0.11	0.00
6	0.11	0.00	0.11	0.00	0.10	0.00
7	0.12	0.00	0.11	0.00	0.09	0.00
8	0.11	0.00	0.10	0.00	0.08	0.00
9	0.12	0.00	0.10	0.00	0.08	0.00
10	0.12	0.00	0.09	0.00	0.07	0.00
Environmental management team			Environmental management training			
1	0.10	0.00	0.10	0.00		
2	0.11	0.00	0.11	0.00		
3	0.11	0.00	0.11	0.00		
4	0.11	0.00	0.11	0.00		
5	0.11	0.00	0.11	0.00		
6	0.10	0.00	0.10	0.00		
7	0.10	0.00	0.10	0.00		
8	0.09	0.00	0.09	0.00		
9	0.09	0.00	0.09	0.00		
10	0.08	0.00	0.08	0.00		

Table 4. Predicted probabilities ROE model (Delta−method).

	Margin	**P > z**	**Margin**	**P > z**	**Margin**	**P > z**
Salary gap predict#(incremental points at 0,0.5,1)			Average employment productivity predict#(incremental points at 0,0.5,1)		Number of women employees predict#(incremental points at 0,0.5,1)	
1.0	0.07	0.00	0.09	0.00	0.07	0.00
1.5	0.10	0.00	0.10	0.00	0.10	0.00
1.1	0.08	0.00	0.06	0.00	0.14	0.00
2.1	0.09	0.00	0.04	0.00	0.08	0.00
2.5	0.10	0.00	0.04	0.00	0.11	0.00
2.1	0.08	0.00	0.06	0.00	0.13	0.00

Table 4. *Cont.*

	Margin	P > z	Margin	P > z	Margin	P > z
3.0	0.10	0.00	0.03	0.00	0.09	0.00
3.5	0.11	0.00	0.00	0.00	0.11	0.00
3.1	0.09	0.00	0.07	0.00	0.12	0.00
4.0	0.11	0.00	0.08	0.00	0.09	0.00
4 5	0.10	0.00	0.09	0.00	0.10	0.00
4.1	0.10	0.00	0.10	0.00	0.11	0.00
5.0	0.10	0.00	0.10	0.00	0.10	0.00
5 5	0.10	0.00	0.10	0.00	0.10	0.00
5.1	0.10	0.00	0.09	0.00	0.10	0.00
6.0	0.10	0.00	0.11	0.00	0.10	0.00
6 5	0.10	0.00	0.10	0.00	0.10	0.00
6.1	0.10	0.00	0.10	0.00	0.09	0.00
7.0	0.09	0.00	0.08	0.00	0.11	0.00
7 5	0.10	0.00	0.10	0.00	0.10	0.00
7.1	0.11	0.00	0.11	0.00	0.09	0.00
8.0	0.08	0.00	0.12	0.00	0.11	0.00
8 5	0.11	0.00	0.13	0.00	0.09	0.00
8.1	0.11	0.00	0.12	0.00	0.08	0.00
9.0	0.08	0.00	0.10	0.00	0.02	0.00
9 5	0.10	0.00	0.13	0.00	0.10	0.00
9.1	0.12	0.00	0.14	0.00	0.07	0.00
10.0	0.07	0.00	0.06	0.00	0.03	0.00
10 5	0.10	0.00	0.10	0.00	0.09	0.00
10.1	0.12	0.00	0.07	0.00	0.07	0.00

Table 4 shows the estimated predicted probabilities for continuous normalized variables taking values in the interval (0,1). To compute the margins, we consider main incremental points at 0, 0.5 and 1. As for the salary gap, the higher the gap the more it positively influences high categories of deciles. In particular, the largest increase is in the figure of +12% at the end point of the 9th decile. A similar result (+14%) appears for the Average employment productivity variable. Finally, we recall the negative sign of the estimated coefficient of the Number of women employees from the model's results. Therefore, we expect larger effects of this variables in low categories of the dependent variable. The positive effects of +14%, +13%, +12% are obtained for the ROE's first, second and third deciles at their end points, respectively.

The findings of the ROA model suggest that the determinants of the probability affecting the ROA and which are statistically significant appear as follows:

- Water efficiency policy (+), Energy efficiency policy (+), Sustainable development policy (+), Environmental innovation score grade (+), Diversity & opportunity policy (+), Salary gap (+), Average board tenure (+);
- Resource use score (−), Environmental management training (−), Environmental innovation score (−), Number of women employees (−), CSR corporate governance board committee (−).

To interpret the results of the magnitudes we refer to the estimated predicted probabilities in Tables 5 and 6. In Table 5, Water and Energy efficiency as well as Sustainable development policies positively affect the forth−tenth ROE decile categories in the range of +10–16%. A similar finding can be found for the Diversity & opportunity policy (+12%) in the fourth−seventh deciles range. In contrast, Environmental management training and CSR corporate governance board committee have large magnitudes in lower classes of the dependent variable such as in the second−fifth deciles (+11–12%).

Table 5. Predicted probabilities ROA model (Delta−method).

	Margin	P > z	Margin	P > z	Margin	P > z
Water efficiency policy			Energy efficiency policy		Sustainable development policy	
1	0.07	0.00	0.07	0.00	0.04	0.00
2	0.08	0.00	0.09	0.00	0.05	0.00
3	0.09	0.00	0.10	0.00	0.06	0.00
4	0.11	0.00	0.12	0.00	0.08	0.00
5	0.10	0.00	0.11	0.00	0.08	0.00
6	0.12	0.00	0.12	0.00	0.11	0.00
7	0.11	0.00	0.11	0.00	0.12	0.00
8	0.11	0.00	0.11	0.00	0.14	0.00
9	0.10	0.00	0.10	0.00	0.15	0.00
10	0.09	0.00	0.09	0.00	0.17	0.00
Diversity & opportunity policy			Environmental management training		CSR corporate governance board committee	
1	0.07	0.00	0.09	0.00	0.12	0.00
2	0.09	0.00	0.10	0.00	0.13	0.00
3	0.10	0.00	0.12	0.00	0.13	0.00
4	0.12	0.00	0.13	0.00	0.13	0.00
5	0.10	0.00	0.11	0.00	0.11	0.00
6	0.10	0.00	0.11	0.00	0.11	0.00
7	0.12	0.00	0.10	0.00	0.09	0.00
8	0.11	0.00	0.09	0.00	0.08	0.00
9	0.10	0.00	0.08	0.00	0.07	0.00
10	0.10	0.00	0.07	0.00	0.06	0.00

Table 6. Predicted probabilities ROA model (Delta−method).

	Margin	P > z	Margin	P > z	Margin	P > z
Environmental innovation score grade predict#(incremental points at 0,0.5,1)			Environmental innovation score predict#(incremental points at 0,0.5,1)		Resource use score predict#(incremental points at 0,0.5,1)	
1.0	0.29	0.00	0.17	0.00	0.07	0.00
1.5	0.14	0.00	0.10	0.00	0.10	0.00
1.1	0.06	0.00	0.06	0.00	0.14	0.00
2.1	0.16	0.00	0.14	0.00	0.08	0.00
2.5	0.12	0.00	0.10	0.00	0.11	0.00
2.1	0.06	0.00	0.06	0.00	0.13	0.00
3.0	0.12	0.00	0.13	0.00	0.09	0.00
3.5	0.11	0.00	0.10	0.00	0.11	0.00
3.1	0.07	0.00	0.07	0.00	0.12	0.00
4.0	0.10	0.00	0.11	0.00	0.09	0.00
4.5	0.10	0.00	0.10	0.00	0.10	0.00
4.1	0.08	0.00	0.08	0.00	0.11	0.00
5.0	0.07	0.00	0.10	0.00	0.10	0.00
5.5	0.08	0.00	0.10	0.00	0.10	0.00
5.1	0.07	0.00	0.09	0.00	0.10	0.00
6.0	0.07	0.00	0.09	0.00	0.10	0.00
6.5	0.10	0.00	0.10	0.00	0.10	0.00
6.1	0.10	0.00	0.10	0.00	0.09	0.00
7.0	0.05	0.00	0.08	0.00	0.11	0.00
7.5	0.08	0.00	0.10	0.00	0.10	0.00

Table 6. *Cont.*

	Margin	P > z	Margin	P > z	Margin	P > z
7.1	0.09	0.00	0.11	0.00	0.09	0.00
8.0	0.05	0.00	0.07	0.00	0.11	0.00
8.5	0.09	0.00	0.10	0.00	0.09	0.00
8.1	0.11	0.00	0.12	0.00	0.08	0.00
9.0	0.05	0.00	0.06	0.00	0.12	0.00
9.5	0.09	0.00	0.10	0.00	0.10	0.00
9.1	0.11	0.00	0.11	0.00	0.07	0.00
10.0	0.04	0.00	0.06	0.00	0.13	0.00
10.5	0.10	0.00	0.10	0.00	0.09	0.00
10.1	0.12	0.00	0.09	0.00	0.07	0.00
Number of women employees predict#(incremental points at 0,0.5,1)			Salary gap predict#(incremental points at 0,0.5,1)		Average board tenure predict#(incremental points at 0,0.5,1)	
1.0	0.06	0.00	0.11	0.00	0.10	0.00
1.5	0.10	0.00	0.09	0.00	0.08	0.00
1.1	0.18	0.00	0.07	0.00	0.05	0.00
2.1	0.07	0.00	0.08	0.00	0.12	0.00
2.5	0.11	0.00	0.10	0.00	0.09	0.00
2 1	0.15	0.00	0.08	0.00	0.06	0.00
3 0	0.08	0.00	0.08	0.00	0.12	0.00
3.5	0.11	0.00	0.11	0.00	0.10	0.00
3.1	0.14	0.00	0.09	0.00	0.08	0.00
4 0	0.09	0.00	0.12	0.00	0.12	0.00
4.5	0.11	0.00	0.10	0.00	0.11	0.00
4.1	0.12	0.00	0.10	0.00	0.09	0.00
5 0	0.09	0.00	0.10	0.00	0.10	0.00
5.5	0.10	0.00	0.10	0.00	0.09	0.00
5.1	0.10	0.00	0.09	0.00	0.09	0.00
6 0	0.10	0.00	0.10	0.00	0.10	0.00
6.5	0.10	0.00	0.11	0.00	0.11	0.00
6.1	0.09	0.00	0.11	0.00	0.10	0.00
7 0	0.11	0.00	0.09	0.00	0.09	0.00
7.5	0.09	0.00	0.10	0.00	0.10	0.00
7.1	0.07	0.00	0.10	0.00	0.11	0.00
8 0	0.12	0.00	0.08	0.00	0.09	0.00
8.5	0.09	0.00	0.10	0.00	0.11	0.00
8.1	0.06	0.00	0.11	0.00	0.12	0.00
9 0	0.14	0.00	0.08	0.00	0.08	0.00
9.5	0.09	0.00	0.10	0.00	0.11	0.00
9.1	0.06	0.00	0.12	0.00	0.14	0.00
10 0	0.16	0.00	0.07	0.00	0.08	0.00
10.5	0.09	0.00	0.10	0.00	0.12	0.00
10.1	0.05	0.00	0.13	0.00	0.17	0.00

Table 6. depicts the estimated predicted probabilities for continuous normalized variables in the interval [0,1]. The computation of the estimated margin values is similar to that illustrated above. As for the Environmental innovation score grade the largest increase is in the figure of +29% at the starting point of the first decile. A similar result appears for the Environmental innovation score in the first (+17%) and second (15%) deciles and Resource use (+14% and +13%, respectively, at incremental point 0.1 in the first and second decile). As for the Number of women employees, the largest effect (+18%) is at the incremental point 0.1 in the first decile. Finally, the largest magnitudes of the Salary gap and the Average board tenure are obtained between the eight−tenth deciles (+12–17%) at the incremental point 0.1.

5. Discussion

This section discusses the aims of this study in the light of the obtained results. We will start with Aim #1 which asserted 'To predict the accuracy of main financial indicators such as the expected Return of Equity (ROE) and Return of Assets (ROA) of public enterprises in Europe based on ESG indicators and other economic metrics.' To respond to Aim #1 we employed ML models to train and test our data such as Random forest, Support Vector Machine (SVM), k−NN, Artificial Neural Network (ANN) and ridge regression. The main findings suggested that most of the above algorithms would perfectly predict both ROE and ROA and that the predictions performed better than the baseline (the median value model). This result appears in line with other studies using ML models in financial markets. In particular, Hernandez−Perdomo et al. [10] derive, through an ML method, a reliability structure function to model CSR. The work considers CSR as a complex system including mechanisms and practices of reporting and transparency and performances. The company−specific conditions define a structure function to link the practices with the performances. This relationship is driven by the growth opportunities of the companies which, in turn, increase with the degree of transparency and reporting.

Hřebíček et al. [59] also use an ML model of neural network in support of the positive effect between CSR practices and economic indicators of a company. In the work the authors argue that ML is a useful tool to identify future trends of economic modelling of CSR and ESG metrics. More recently, Samitas et al. [60] use an ML approach to predict financial crises and provide significant information to policy makers and investors about employing a structured financial network to avoid loss of earnings of the financial portfolio.

Aim #2 addressed 'To identify whether ESG initiatives affect the financial performance of public European enterprises' with the use of logistic regression models. Although some of our predictor variables were not statistically significant, we can argue that the identified factors in response to Aim #2 are aligned with the current literature and similar contexts discussed below.

From the inferential analysis, the first of our findings is that Sustainable development policy, Diversity & opportunity policy and the Salary gap positively affect both the ROE and ROA in the range of +10%–16% between the fourth and tenth deciles. A similar result is obtained for Water and Energy efficiency policies on the ROA, whereas the Environmental innovation score grade provides the largest increase of ROA (+29%, particularly in the first decile). In addition, the Average board tenure positively affects the ROA (+12%–17%) in the eight−tenth deciles. This means that investors appreciate the knowledge and expertise gained by the board representatives over time and increase their trust provided the stability of the company's governance.

Several studies examine the relationship between energy consumption and economic/financial growth at the firm level. Subrahmanya [61] finds that energy makes a significant contribution to the economic performance of firms. In other words, companies with less energy intensive activities achieve higher returns. Bunse et al. [62] argue that an improvement in energy efficiency initiatives increases the performance of the economic and financial metrics of the firm, increases output productivity and reduces the payback of the investments. The importance of energy efficiency policies is recognized by the recent study of Fan et al. [63]. The authors consider the evidence provided by Chinese energy−intensive firms on the relationship between energy efficiency performance and financial indicators such as, among others, ROE and ROA. The authors' results show that high energy efficiency firms can provide better financial performances and suggest that investments in energy efficiency is vital for firms that have both market pressures and potentials of growth and development.

In terms of diversity, social inclusion and opportunity disclosures, Labidi and Gajewski [64] consider these intangible assets, among others, as effective indicators through which investors can gain more information and firms enhance their capability to provide stock liquidity with new equity offers. In addition, to strengthen the relevance of diversity and opportunity in our findings, the study by Bennouri et al. [65] emphasize the positive relationship between female directorship and firms' financial accounting indicators such as ROA and ROE in the French context. The authors suggest that female leadership positions and their education are positively correlated with ROE and ROA.

Furthermore, the authors suggest that the relationship between corporate strategic management decisions, including diversification and social inclusion opportunities and financial performances are sensitive to the attributes (e.g., reputation, independence) of female directors. A recent investigation of Sharma et al. [66], shows that workforce racial diversity assumes a U−shaped relationship affecting a company's CSR performance. According to the authors, this is a relevant aspect since CSR is considered an important indicator in the current business world. Also, the authors suggest '*that a racially diverse workforce brings the logic of community, which would significantly change an organization's response to its corporate social responsibility*' [66] (p.149).

In terms of Average employment productivity, it positively affects the ROE in the magnitude of +14% in the ninth decile. This result indicates that increases of employment productivity not only reflect a good company's management but are particularly relevant in high ranked ROE ratios.

The second of our findings is that Environmental management training, Number of women employees and CSR corporate governance board committee negatively affect both ROE and ROA. The negative sign of the estimated coefficients of the predicted probabilities should be interpreted with caution because larger effects of the above predictors are more relevant in the first decile classes of the ROE and ROA. As a result, the above variables affect our predictors in the range of +11–18% between the first and fifth decile (i.e., in relatively low−middle performance ratios of ROE and ROA).

Similar findings can be found for the Environmental management team (+11%) in the third and fourth decile of the ROE, Resource use (14% and 13%) and Environmental innovation score (+15%–17%) in the first two deciles of the ROA. We argue that large investments occur, in line with the current debate [67], to employ environmental engineers and managers with excellent expertise in the management of environmental goods, as well as to implement environmental innovations and resource use efficiency in the company. As a result, although in accordance with current sustainable development strategies, these investments may be costly and require long−term financial commitments and hence, affect the performance of the ROE and ROA. Therefore, the magnitude of the above investments may be larger on lower ratios of these indicators. Fakoya [68] analyses the case of hazardous solid waste strategies in 64 firms listed on the Social Responsibility Investment Index of the Johannesburg Stock Exchange from 2008 to 2017. The main findings indicate that long−term investments in hazardous solid waste reduction would not significantly affect ROA. In addition, the study by Agyabeng−Mensah et al. [69], which conducted structured questionnaires in 240 firms across three industries (entertainment, manufacturing and logistics) and a structural equation model, asserts that in particular supply chain sectors such as logistic activities, green logistics practices requiring substantial investments do not have a particular influence on the financial performance of firms, in the short/medium run. In contrast, the recent evidence by Lin et al. [70] which considers ESG data for a sample of 163 firms over the period 2011–2017 suggests that environmental innovation strategies show statistically significant positive impacts on ROE and ROA.

Finally, in Aim #3, we intended 'To discuss how ESG factors, based on the findings of Aims #1 and #2, can contribute to the advancements of the current debate on CSR policies and practices in public enterprises in Europe.' To respond to Aim #3, we consider a discussion which highlights relevant policy implications for the three main ESG indicators which appeared most influential on ROE and ROA—1. Environmental innovation; 2. Employment productivity; and 3. Diversity and opportunity.

Environmental innovation. In the last decades, the competitive advantage of firms has been characterized by the increasing attention to green innovations. This competitive advantage is affecting the financial performance of firms, although the scale and magnitude of these effects may vary according to the industry, the legal norms and the social acceptance to renewable technologies [71–73]. To achieve the strict environmental and emission reduction targets, particularly in the European Union, member states should address or re−address, in the next decades, technological systems, products and processes as well as consumer behaviors. On the other hand, the financial performance of firms may, in turn, have influences on the companies' CSR strategies and environmental performance [74]. Accordingly, companies with a good financial performances can allocate more resources to environmental innovation investments. Understanding these relationships help the policy maker to provide new insights on the degree of environmental innovation needed in the market, to raise awareness among stakeholders and consumers. Recently, the New Green Deal For Europe [75] can be crucial to boost environmental innovation in European companies as well as contribute to the future transformation of the European economy in a sustainable society. In fact, it is a clear roadmap with key actions to 2050 in response to tackling climate and environmental−related challenges and will require a significant investment of about 1 trillion Euros which will mobilize public resources and unlock private resources [76].

Employment productivity. Productivity measures the firm's ability to use its input factors efficiently and convert them into useful outputs. Microeconomic textbooks teach us that an increase in the productivity leads to better profitability of the firms thanks to the decreasing of the unit production cost [77]. Among the input factors affecting the unit production cost, labor is an essential element. The labor market, particularly in Europe, has gone through a number of structural adjustments due to either the market structure of national economies, the competition of foreign businesses or external shocks (i.e., the recent COVID−19 emergency, migration fluxes from neighboring countries and the 2008–2018 economic crisis). Nonetheless, European companies that aim at improving or increasing their long−term financial and economic performance should improve their labor productivity. '*Labor productivity can be increased by appropriate incentive mechanisms and by building a good working environment for employees*' [78] (p. 137). In its Council Decision n. 1215 of 2018, the Council of the European Union [79] has set new guidelines for employment policies of the member states. These guidelines are based on the European pillar of social rights (see below) which includes 20 principles aiming at achieving equal opportunities and access to the labor market, fair working conditions and social protection and inclusion of workers. The Council decision reflects a new policy approach which provides long−term investments, structural reforms and fiscal actions and responsibilities of member states. These measures should increase job opportunities particularly driven by education, training activities and promotion of equal opportunities and translate them into increases of employment productivity and business financial performances.

Diversity and opportunity. Nowadays, diversity and equal opportunity policies are key elements towards the implementation of an efficient CSR strategy. According to the European Commission [80], the new concept of diversity and inclusion goes beyond the issues of ensuring compliance with non−discrimination and equality. It refers to a wider and proactive approach through which it is possible to create a diverse working environment and an inclusive culture where individuals feel values and release their skills and potentials in the workplace. In fact, diversity and equal opportunity promotes value added to the firms and the society as a whole [81]. As already said, European businesses need to overcome the limitations of the labor market due to the lack or mismatch of skills and face international competitors. The promotion of diversity and equal opportunities also produces several effects in terms of innovation initiatives, competitiveness within national and international markets, creativity and reputation. To strengthen CSR strategies and improve financial performances, companies can promote diversity at various levels such as increasing horizontal integration, creating learning−work environment, enhance network collaborations and team working and participation in the company's decision making process [82]. In conclusion, diversity and equal opportunities allow firms to efficiently allocate their resources and create a multicultural environment for employment productivity and exceptional business performances.

6. Conclusions

The present work explored whether ESG company's practices can lead to better financial performances of public enterprises.

We performed a case study of 1038 public companies in Europe and applied a combined analysis with machine learning and logistic regression models. Both tools were employed to investigate two financial indicators such as ROE and ROA in the fiscal year 2018–2019. Machine learning models investigated the accuracy of ROE and ROA based on ESG and other economic indicators; while logistic regression models examined whether ESG factors affected the performance of these financial metrics.

Main findings suggested that both ROE and ROA would be perfectly predicted by most ML algorithms and that predictions performed better than the baselines. This result allowed us to argue in support of a relationship between the ESG variables and the financial performances of ROE and ROA. Therefore, the application of a logistic regression model on the normalized and discretized data from the ML study tested the above relationship. The main findings suggested to focus our discussion of policy implications on the following ESG issues—Environmental innovation, employment productivity and diversity and equal opportunity.

As a result, the recent European New Green Deal and circular economy policies and visions may foresee challenging socio−economic and environmental implications driven by the development of CSR policies and practices to implement future sustainable development policies in public enterprises.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Total number of firms per country and GICS classification.

	Freq.	Percent
Countries		
Austria	19	1.83
Belgium	19	1.83
Cyprus	5	0.48
Czech Republic	5	0.48
Denmark	36	3.47
FaROE Islands	1	0.10
Finland	37	3.56
France	82	7.90
Germany	118	11.37
Gibraltar	1	0.10
Greece	12	1.16
Guernsey	1	0.10
Hungary	4	0.39
Republic of Ireland	28	2.70
Isle of Man	3	0.29
Italy	43	4.14
Jersey	5	0.48
Luxembourg	15	1.45
Malta	3	0.29
Monaco	4	0.39
Netherlands	41	3.95
Norway	33	3.18
Poland	30	2.89

Table A1. *Cont.*

	Freq.	Percent
Portugal	6	0.58
Romania	2	0.19
Russia	20	1.93
Spain	46	4.43
Sweden	80	7.71
Switzerland	81	7.80
Ukraine	1	0.10
United Kingdom	257	24.76
Total	1038	100.00
GICS Sectors		
Communication Services	76	7.32
Consumer Discretionary	126	12.14
Consumer Staples	63	6.07
Energy	61	5.88
Financials	171	16.47
Health Care	77	7.42
Industrials	203	19.56
Information Technology	60	5.78
Materials	94	9.06
Real Estate	65	6.26
Utilities	42	4.05
Total	1038	100.00

Table A2. Description of the dataset.

Variable name	Category	Description
Emission score	Environmental	Continuous variable. In %
CO_2 equivalent emissions	Environmental	Continuous variable. In million CO_2 equivalent
Resource use score	Environmental	Continuous variable. In %
ESG score	Environmental	Continuous variable. In %
ESG score grade	Environmental	Categorical variable
Water efficiency policy	Environmental	Binary variable. 1=presence 0=absense
Energy efficiency policy	Environmental	Binary variable. 1=presence 0=absense
Sustainable development policy	Environmental	Binary variable. 1=presence 0=absence.
Environmental management team	Environmental	Binary variable. 1=presence 0=absence
Environmental management training	Environmental	Binary variable. 1=presence 0=absence
Environmental innovation score	Environmental	Continuous variable. In %
Environmental innovation score grade	Environmental	Categorical variable
Diversity & opportunity policy	Social	Binary variable 1=presence 0=absense
Salary gap	Social	Continuous variable. Mean hourly pay gap between male and female employees
Number of employees in the CSR reporting	Social	Continuous variable. In thousands
Number of women employees	Social	Continuous variable. In %
Workforce score	Social	Continuous variable. In %
Human rights score	Social	Continuous variable. In %
Product responsibility score	Social	Continuous variable. In %

Table A2. *Cont.*

Variable name	Category	Description
Average employment productivity	Social	Continuous variable in thousand Euros
Health & safety policy	Governance	Binary variable. 1=presence 0=absence
Training and development policy	Governance	Binary variable. 1=presence 0=absence
Career development policy	Governance	Binary variable. 1=presence 0=absence
CSR sustainable development committee	Governance	Binary variable. 1=presence 0=absence
CSR corporate governance board committee	Governance	Binary variable. 1=presence 0=absence
Average board meeting attendance	Governance	Continuous variable. In number of days/yr (avg)
Average board tenure	Governance	Continuous variable. In number of years
Management score	Governance	Continuous variable. In %
CSR strategy score grade	Governance	Categorical variable
CSR strategy score	Governance	Continuous variable. In %
Change in company market cap	Financial	Continuous variable. In % change from previous year
Operating income	Financial	Continuous variable in million Euros
Net income	Financial	Continuous variable in Billion Euros
Change in total equity	Financial	Continuous variable. In % change from previous year
Return on Equity (ROE)	Financial	Continuous variable. In %
Return on Assets (ROA)	Financial	Continuous variable. In %

Table A3. Legend of the models used in Figure 1.

Model Name	Description
ROA median	Prediction of ROA according to a model that always predicts the median ROA value seen during testing
ROA random	Prediction of ROA according to a model that predicts a uniformly random value from those seen during testing
ROA forest	Predicted ROA using a Random forest
ROA svm	Predicted ROA using a Support Vector regression
ROA 2nn	Predicted ROA using a k−nearest neighbors model with k=2
ROA 10nn	Predicted ROA using a k−nearest neighbors model with k=10
ROA 20nn	Predicted ROA using a k−nearest neighbors model with k=20
ROA ann	Predicted ROA using an artificial neural network model
ROA ridge	Predicted ROA using ridge regression
ROE median	Prediction of ROE according to a model that always predicts the median ROE value seen during testing
ROE random	Prediction of ROE according to a model that predicts a uniformly random value from those seen during testing
ROE forest	Predicted ROE using a Random forest
ROE svm	Predicted ROE using a Support Vector regression
ROE 2nn	Predicted ROE using a k−nearest neighbors model with k=2
ROE 10nn	Predicted ROE using a k−nearest neighbors model with k=10
ROE 20nn	Predicted ROE using a k−nearest neighbors model with k=20
ROE ann	Predicted ROE using an artificial neural network model
ROE ridge	Predicted ROE using ridge regression

Table A4. Ordered logistic regression. ROE estimates.

ROE	Coef.	St.Err.	t-Value	*p*-Value	[95% Conf.	Interval]	Sig
Emission score	0.29	0.39	0.74	0.46	−0.47	1.04	
Resource use score	0.21	0.48	0.44	0.66	−0.73	1.16	
ESG score	−0.14	2.27	−0.06	0.95	−4.59	4.32	
ESG score grade	−0.45	1.88	−0.24	0.81	−4.14	3.23	
Water efficiency policy	−0.01	0.14	−0.10	0.92	−0.28	0.25	
Energy efficiency policy	0.25	0.21	1.20	0.23	−0.16	0.66	
Sustainable development policy	0.40	0.15	2.61	0.01	0.09	0.69	***
Environmental management team	−0.26	0.14	−1.86	0.06	−0.52	0.01	*
Environmental management training	−0.34	0.14	−2.47	0.01	−0.60	−0.07	***
Environmental innovation score grade	0.88	1.20	0.74	0.46	−1.46	3.23	
Environmental innovation score	−1.87	1.30	−1.44	0.15	−4.41	0.68	
Diversity & opportunity policy	0.80	0.28	2.86	0.00	0.25	1.35	***
Salary gap	0.56	0.20	2.87	0.00	0.18	0.95	***
Number of employees in the CSR reporting	−0.41	0.33	−1.24	0.21	−1.07	0.24	
Number of women employees	−0.76	0.33	−2.29	0.02	−1.41	−0.11	**
Workforce score	0.38	0.46	0.82	0.41	−0.52	1.28	
Human rights score	−0.38	0.30	−1.27	0.20	−0.97	0.21	
Product responsibility score	0.08	0.27	0.30	0.77	−0.45	0.61	
Average employment productivity	1.24	0.37	3.36	0.00	0.52	1.97	***
Health & safety policy	−0.13	0.24	−0.56	0.58	−0.60	0.33	
Training and development policy	−0.60	0.40	−1.50	0.13	−1.38	0.19	
Career development policy	0.34	0.33	1.04	0.30	−0.30	0.99	
CSR sustainable development committee	0.07	0.16	0.41	0.68	−0.25	0.38	
CSR corporate governance board committee	−0.41	0.14	−2.87	0.00	−0.69	−0.13	***
Average board meeting attendance	0.89	0.88	1.01	0.31	−0.83	2.60	
Average board tenure	−0.04	0.40	−0.10	0.92	−0.82	0.74	
Management score	0.14	0.43	0.32	0.75	−0.70	0.97	
CSR strategy score grade	−0.50	1.04	−0.48	0.63	−2.55	1.55	
CSR strategy score	0.41	1.17	0.35	0.72	−1.87	2.69	
Mean dependent var	4.51		SD dependent var		2.87		
Pseudo r−squared	0.02		Number of obs		1038		
Chi−square(29)	101.67		Prob > chi2		0.00		
Brant test Chi−square(232)	254.92		Prob > chi2		0.18		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. Ordered logistic regression. ROA estimates.

	Coef.	St.Err.	t-Value	*p*-Value	[95% Conf	Interval]	Sig
Emission score	0.02	0.39	0.04	0.97	−0.74	0.77	
Resource use score	−0.94	0.48	−1.97	0.05	−1.87	−0.01	**
ESG score	1.65	2.26	0.73	0.47	−2.78	6.09	
ESG score grade	−0.88	1.85	−0.48	0.63	−4.51	2.75	
Water efficiency policy	0.34	0.14	2.53	0.01	0.08	0.60	***
Energy efficiency policy	0.50	0.21	2.44	0.01	0.10	0.91	***
Sustainable development policy	0.96	0.15	6.26	0.00	0.66	1.26	***
Environmental management team	−0.07	0.14	−0.52	0.60	−0.34	0.20	
Environmental management training	−0.37	0.14	−2.73	0.07	−0.64	−0.10	*
Environmental innovation score grade	2.14	1.24	1.73	0.08	−0.28	4.57	*
Environmental innovation score	−3.68	1.36	−2.71	0.01	−6.34	−1.02	***
Diversity & opportunity policy	0.59	0.27	2.19	0.03	0.06	1.12	**
Salary gap	0.67	0.20	3.40	0.00	0.28	1.06	***
Number of employees in the CSR reporting	−0.14	0.33	−0.41	0.68	−0.78	0.51	
Number of women employees	−1.41	0.33	−4.22	0.00	−2.06	−0.75	***
Workforce score	0.19	0.46	0.42	0.67	−0.70	1.09	
Human rights score	−0.23	0.30	−0.77	0.44	−0.81	0.35	
Product responsibility score	0.15	0.27	0.55	0.59	−0.38	0.68	
Average employment productivity	−0.05	0.36	−0.15	0.88	−0.76	0.66	
Health & safety policy	0.11	0.24	0.44	0.66	−0.37	0.58	
Training and development policy	−0.40	0.40	−1.00	0.32	−1.18	0.38	
Career development policy	0.07	0.32	0.21	0.84	−0.57	0.70	
CSR sustainable development committee	0.01	0.17	0.07	0.95	−0.31	0.34	
CSR corporate governance board committee	−0.57	0.15	−3.92	0.00	−0.85	−0.28	***
Average board meeting attendance	0.33	0.83	0.39	0.69	−1.30	1.95	
Average board tenure	0.89	0.40	2.21	0.03	0.099	1.67	**
Management score	−0.15	0.43	−0.35	0.73	−0.99	0.69	
CSR strategy score grade	−1.02	1.05	−0.97	0.33	−3.08	1.04	
CSR strategy score	0.97	1.17	0.83	0.41	−1.32	3.26	
Mean dependent var	4.55		SD dependent var		2.86		
Pseudo r−squared	0.04		Number of obs		1038		
Chi−square(29)	170.24		Prob > chi2		0.00		
Brant test Chi−square(232)	261.05		Prob > chi2		0.11		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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